9-4-2017

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Recommended Citation

Reiter-Palmon, R., Sinha, T., Gevers, J., Odobez, J., & Volpe, G. (2017). Theories and models of teams and groups. Small Group Research, 48(5), 544-567. https://doi.org/10.1177/1046496417722841

Theories and Models of Teams and Groups

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Abstract

This article describes some of the theoretical approaches used by social scientists as well as those used by computer scientists to study the team and group phenomena. The purpose of this article is to identify ways in which these different fields can share and develop theoretical models and theoretical approaches, in an effort to gain a better understanding and further develop team and group research.

Keywords

social science, computer science, interdisciplinary research, theory

The purpose of this article is to provide a review of how scholars from computer sciences and social sciences may join forces to conduct interdisciplinary group research that may simultaneously advance both fields. To facilitate collaboration and true interdisciplinarity in the study of groups, a number of issues need to be addressed.

First, computer scientists need to have a better understanding of the theories developed by social scientists and vice versa. Theories and approaches used in the respective fields have typically been developed independently and may appear rather disparate, at least initially. Having a better understanding of each other's approaches is indispensable for any form of cross-pollination or integration to occur. Therefore, we begin this article with a discussion of some of the main theoretical frameworks and perspectives used by social scientists and computer scientists when examining group or team phenomena. These theories have been selected based on two criteria. One, we selected theories that are broad and include a wide range of phenomena so that they can be useful to the multiple perspectives and areas of research of social science and computer science. Two, we selected theories that we thought would be best suited to the phenomena of interest of both computer and social scientists.

Second, having social scientists using computer science theories and models, and computer scientists approaching research using social science theories and models may facilitate additional learning by the respective fields. Major advancements, though, will require the development of a shared theoretical perspective—one that is not based in one field, but spans both, to guide interdisciplinary research that is truly integrative in nature. Therefore, our second step is to offer an example of how insights from computer science and social science may be fruitfully integrated to pose meaningful research questions that may contribute to a shared framework for understanding group phenomena. Here, the focus is on the case of computer-supported group work, but we believe that several of these questions apply to other group analysis studies as well. While this is used for illustrative purposes, there are many more phenomena that can be studied using this approach (e.g., dynamic nature of interactions, human–computer interactions).

Third, in addition to bridging theoretical perspectives, it is important to note that differences in methodologies between fields (which are fully addressed in another article in this special issue) are also relevant here. These methodologies are likely to influence the complexity and specificity of the phenomenon being studied and theoretical approaches used. This article concludes with a brief discussion of how methodological issues related to dynamics and unit of analysis in group research may complicate the development of a unified approach. In light of this issue, we address the need to find an appropriate balance that allows for an advancement of research questions that are both theoretically meaningful and methodologically feasible.

Social Science Framework for Studying/Group Phenomena

In the social sciences, the typical approach for studying group phenomena is that of the input–process–output (IPO) model (Kozlowski & Ilgen, 2006; Salas, Burke, & Stagl, 2004). Although this is not the only framework for understanding teams and team performance, this model has been researched considerably and received wide support across disciplines (Kozlowski & Ilgen, 2006). The IPO model suggests that to understand teams and team functioning, attention must be given to the inputs into the team environment, the processes that teams engage in, and the outputs of the team. In terms of inputs, team composition has been studied extensively. Specifically, aspects such as demographics (i.e., age, gender, race), educational background, and functional diversity as well as personality diversity have been evaluated (Reiter-Palmon, Wigert, & de Vreede, 2011). Inputs also include environmental aspects such as organizational context variables. Processes are the activities that team members engage in to solve the problem or carry out the task such as problem-solving activities, planning, and social processes such as conflict management and developing trust. Recently, it has been suggested that many of these processes can be conceptualized as emergent states, that is, they emerge as a result of interactions among the team members (Kozlowski &

Klein, 2000; Marks, Mathieu, & Zaccaro, 2001). Kozlowski and Klein (2000) defined emergence as a phenomenon that “originates in the cognition, affect, behaviors, or other characteristics of individuals, is amplified by their interactions, and manifests as a higher-level, collective phenomenon” (p. 55). Examples of emergent states that result from the interactions between team members are trust, cohesiveness, leadership, collective efficacy, as well as shared mental models and transactive memory system. Finally, the output is the outcome of interest to many researchers and can include team effectiveness, viability, team performance, creativity, and so on, and also individuallevel outcomes such as team member satisfaction, well-being, individual performance, and turnover intention.

Empirical work utilizing this approach has formed the basis of additional refinement and understanding of the framework, but the framework itself is fairly broad. Within the framework, though, there is some discussion regarding how various components should be conceptualized (Moreland, Levine, & Wingert, 1996). For example, when evaluating input, early work focused on the assessment of team homogeneity or diversity with regard to demographic variables (Mannix & Neale, 2005), which were typically evaluated one variable at a time (e.g., race, gender). Later, it has been suggested that less observable demographic variables should be included such as educational background or function in the organization (Fay, Borrill, Amir, & West, 2006). Personality characteristic diversity has also been evaluated (Barrick, Stewart, Neubert, & Mount, 1998; Peeters, van Tuijl, Rutte, & Reymen, 2006). With the addition of such variables, it became clear that the definition of team diversity is not as well-defined or clear-cut as originally thought (Harrison & Klein, 2007). There are multiple ways in which to evaluate team diversity, and the effect of diversity can vary depending on the outcome. For example, demographic diversity seems to influence team social processes adversely, at least initially (Williams & O’Reilly, 1998). The same type of diversity seems to have little effect on the outcome of creativity (Hulsheger, Anderson, & Salgado, 2009).

The research on processes tended to focus mainly on social processes. Early work evaluated the role of communication and communication patterns on various outcomes, and as a mediator between team input and outcomes. Later work has focused more on emergent states such as trust. An important issue in this context is whether these process variables are conceptualized (and measured) at the team level or the individual level (Bliese, 2000; Kozlowski & Klein, 2000). For example, trust is typically measured at the individual level. To obtain a team-level phenomenon, researchers aggregate trust to the team level. When researchers do this, they first must determine that the variable of interest can be aggregated, that is, that there is group agreement on this construct. At that point, researchers move away from individual perceptions of trust to a team construct. More recently, researchers have also evaluated the role of more cognitive processes, in terms of social cognition (i.e., cognition about teams), such as shared mental models (DeChurch & Mesmer-Magnus, 2010; Mohammed, Ferzandi, & Hamilton, 2010) or transactive memory systems (Lewis, 2003;

Zhang, Hempel, Han, & Tjosvold, 2007). In addition, cognitive processes associated with decision making and problem solving, such as idea generation or idea evaluation, have also been studied (Reiter-Palmon, Herman, & Yammarino, 2008).

Despite the inherent dynamic nature of the IPO model, early research conducted on teams using this framework employed a snapshot approach, studying the relationships between inputs, processes, and outcomes at a single point in time. Now, researchers are increasingly advocating and applying longitudinal and dynamic approaches in which input, process, and output variables are assessed repeatedly (or even continuously) over a certain period of time. This allows researchers to assess (natural) dynamics in team input variables (e.g., due to membership change) and capture the emergence of particular processes and emergent states, such as team cohesion and shared cognition (Kozlowski & Chao, 2012; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2013). Moreover, besides studying the role of input and process factors on team outcomes, researchers are now increasingly interested in how and under what conditions do team outcomes impact input and process factors, such as how initial performance may instigate certain upward or downward spirals in team relations and team effectiveness (Ilgen, Hollenbeck, Johnson, & Jundt, 2005).

Computer Science Framework for Studying Group Phenomena

Computer science approaches to studying group phenomena have a technological and computational perspective. From a broad perspective, technological aspects benefit of advancement in new sensors, miniaturization, power consumption, and so on (Hof, 2013). Research questions focus on whether, and under which conditions, or in which social and environmental situations sensors are appropriate and an effective way to measure or recognize activity and behavioral information, especially for pervasive sensors (Ranasinghe, Al Machot, & Mayr, 2016). The computer science framework also includes fusing and comparing the benefits of different modalities for sensing a similar cue like using small embedded gyroscopes instead of images to measure body or head orientation, or different sports activities (Mendes, Vieira, Pires, & Stevan, 2016).

The computational aspect is linked to the machine learning (ML) perspective or artificial intelligence. Fundamentally, the goal is to learn from training data a mapping function Output = fmap(Input, theta). Theta is a parameter of the mapping function. In this perspective, outputs are the behavioral variables of the individual or team that are of interest for researchers and which often would require lengthy or tedious manual annotation or expert knowledge to be derived (and are therefore not available when dealing with a new individual, team, or group). On the contrary, the inputs are observations or measurable variables that can be automatically extracted from sensor data and might have a predictive power for the targeted output. For example, the inference of an individual’s positive stance in a social interaction can be determined by examining his or her slight bending forward toward the conversational partner. More generally, in practice, the mapping can correspond to the prediction of categories, regression toward any value (e.g., intensity of an emotion, level of satisfaction, or any Likerttype output in general), or multidimensional combination of these. Examples of output categories can refer to short-term communication acts (e.g., who has the floor and what action is performed—holding it, release it, floor grabbing attempts; or who is addressed), interaction and individual state at different levels of temporal granularity (Is the person smiling, engaged, attentive? What are her personality traits?), or to the group as a whole (e.g., cohesion; Gatica-Perez, 2009; Gatica-Perez, Vinciarelli, & Odobez, 2014). Importantly, the output can range from more objective (i.e., Is she speaking? Is she looking in that direction?) to more subjective (Is she the leader? Do they like each other? Is the team effective?), which usually requires some form of evaluation.

ML methods are not new. The fmap functions include decision trees, boosting methods, naive Bayesian techniques, and so on. Among these, Bayesian approaches have also been used more extensively. These techniques allow us to explicitly represent the variables of interests, their relation, uncertainties, and therefore provide some interesting interpretative and reasoning properties. In conjunction with recent advances in inference, they have produced good results, especially when modeling dynamical data.

However, in recent years, deep learning techniques (Hof, 2013) combined with a large increase in data availability and computing power have revolutionized data processing. They have been shown to surpass, often by a large margin, previously existing methods in many fields and for many tasks, including those related to human behavior analysis. In this view, audio processing and speech recognition, text understanding, and video analysis (e.g., face detection, head orientation, expression recognition, gesture recognition) have shown tremendous progress. This makes them accessible and robust enough to automatically process and extract social cues in much less controlled situations and conditions (often called in the wild in the computer science domain) than before. The creation of public benchmark data (e.g., kaggle.com), often associated with computational challenges, has also greatly helped in making progresses.

Nevertheless, in spite of this progress, ML techniques suffer from several issues which could benefit from more insight from group theories:

- Curse of dimensionality of social phenomenon: ML techniques like deep learning require relatively large amounts of data to be effective. For dynamical data involving interactions in the wild (i.e., in more ecological settings, in many different contexts), this is a difficult task, especially for collecting labels about group attributes from social scientists. Given that ML techniques expect patterns that are repeatable enough to generalize, this is an important issue.

- Interpretability: ML approaches may just act as predictors of some variable, without providing any cause, or any modeling insight regarding what is going on in a group. To avoid this, interpretability of ML methods becomes a key issue for advancing the research. On one hand, it places ML findings in the context of the social science group literature. For instance, ML can identify which are the best behavioral cues that are able to predict a social outcome, which can then be compared with previously reported features extracted manually and often with much less data in the literature. On the other hand, it may allow discoveries (new multimodal features jointly achieving better performance than features from previous theories) that can improve or further motivate theoretical work in the social science study of groups.

• Generalization: While ML methods can help to define which of the inputs seem more relevant or which of the outputs are more predictable for a given task and in a given context, most of the time they cannot model the involved processes (task performed by a group). Rather, these methods often merely use processes as implicit context. That is, the prediction model is learned for the defined task and scenario, which are often controlled to isolate specific effects. They thus may work under these specific conditions, but usually will not generalize well beyond the experiment at hand.

• Understanding: ML can recognize and measure well the observable nonverbal cues (e.g., facial expressions, basic emotions, amount of interaction) and, to some extent, the impression it makes on people. However, modeling inner states in a more general model of the theory of mind has by far not been achieved yet (Byom & Mutlu, 2013). Moreover, whereas ML methods work well for modeling and predicting states, they are currently somewhat less suited to model complex multimodal processes developing over time.

• Representations: A general consequence of the above elements is that ML should not rely on computational methods and representations that attempt to directly predict high-level outcomes (e.g., group performance) from low-level cues (e.g., speaking turns, interruptions, number of smiles). Rather, the learned representation should also be able to predict complementary concepts (e.g., participant behaviors, dyadic relational attitudes, group cohesion) to structure what it has to learn and what it learned. Such concepts should preferably be interpretable. Social science theories can be beneficial in creating a list of these concepts and their definitions.

Opportunities for Interdisciplinary Research

Although scholars from both social and computational sciences aim to study group phenomenon, it is clear from the central frameworks and approaches described above that the two fields are worlds apart. Still, much may be won from bringing these worlds closer together. Opportunities for interdisciplinary research in studying cognitive processes and other social processes in groups can arise from analyzing complementarity between affordances of traditional psychometric approaches (e.g., self-reported questionnaires), as well as qualitative approaches (video or audio coding, content analysis), and computational approaches in language technologies, human–computer interaction, ML, and social network analysis.

The study of shared mental models in teamwork provides an example of how scholars from both fields investigate the same phenomenon. Although mental models are fundamentally internal, dynamic, and incomplete, researchers in both group science and computer science have attempted to externally represent them to better understand people's representation of concepts and their interrelationships (Novak & Cañas, 2006). Typically, group members themselves create these maps by choosing concepts from a predetermined list or filling blanks in a given conceptual structure (Chang, 2007). However, these self-created approaches have several issues. First, they are time-consuming to manually create and evaluate post hoc. Second, the metacognitive act of creating concept map representations may introduce bias from an individual's awareness of being assessed (Andersen, Richardson, & Vennix, 1997). Third, these maps may be inconsistent when created by the same individual over time. To address these issues in creation and evaluation of shared mental models that are instantiated in the form of concept maps (Kinchin, Hay, & Adams, 2000; Ruiz-Primo & Shavelson, 1996), the field of computer science offers a range of automatic and semiautomatic approaches to dynamically extract shared concept maps from verbal transcripts of group member conversations. This allows the discovery of both proximal and semantic relationships between usage of concepts, thus favoring reproducibility, speed, and scalability (Carley, Bigrigg, & Diallo, 2012). Combining such advanced network text analysis approaches with complementary approaches inspired by linguistics and psychology (e.g., Coh Metrix, Graesser, McNamara, Louwerse, & Cai, 2004; Linguistic Inquiry and Word Count [LIWC], Tausczik & Pennebaker, 2010; Wordnet-Based Semantic Cohesion, Ward & Litman, 2008) provides opportunities for gaining additional insights into how shared mental models, evidenced by shared concept maps, manifest in verbal behaviors over time. In addition to verbal modality, opportunities for cross-cutting interdisciplinary research also arise from analyzing complementary affordances provided by paralinguistic, visual, and vocal modalities. Furthermore, a holistic view of interpersonal communication dynamics can be developed using approaches for studying multimodal synchronization among team members (Delaherche et al., 2012; Reidsma, Nijholt, Tschacher, & Ramseyer, 2010; Sinha & Cassell, 2015).

Such opportunities allow us to move out of the lab and study models in more ecologically valid settings by using advances in sensors and computation to collect field data of interaction in naturally occurring groups over longer periods than those possible in the lab. By augmenting (rather than replacing) traditional sources of information such as surveys and performance data with the analysis of digital communication means, such as emails and behavioral sensor data like amount of face-to-face interaction or speaking time, it is possible to analyze group interactions in a different way (Olguín et al., 2009). This allows us to effectively design interventions aimed at enhancing team performance and analyze their effects more precisely (Olguín & Pentland, 2010).

At the same time, social sciences represent a major source of knowledge and inspiration for computer sciences and can inform research and technological development in computer sciences. Social science research concerning organizations, organizational processes, and teamwork can provide insights on (a) which data to collect (behavioral cues, relational data, text and verbal messages), (b) how to organize and implement computational processes (e.g., scheduling of processes and devices, management of networks, sharing of computational load among devices), and (c) how to design effective interfaces between computational devices and groups of users. For example, string quartets have been studied in social sciences because their teamwork resembles those in various organizational units, especially self-managed teams (Gilboa & Tal-Shmotkin, 2010; Tal-Shmotkin & Gilboa, 2013). String quartets were also investigated using a human–computer interaction framework with the aim of exploiting behavioral cues of the social interaction among the members of the quartet to inform the design of novel interfaces for group interaction with computers (e.g., Glowinski et al., 2013). At the application level, social sciences can provide a robust scientific base on which to base applications. Social scientific insights regarding the emergence and influence of group interaction processes would certainly aid application development in the areas of serious games, education, therapy, and rehabilitation, as well as in entertainment and performing arts, complementary to insights gained from research fields such as Affective Computing (Picard, 1997) and Social Signal Processing (Vinciarelli, Pantic, & Bourlard, 2009).

In addition to examples of cross-disciplinary fertilization between computational and social sciences, future calls for research on teams should be truly interdisciplinary, not in the least because the nature of teamwork is changing (Tannenbaum, Mathieu, Salas, & Cohen, 2012). The idea of intelligent agents becoming an integral part of groups and teams has grown from a promising vision (Hinds, Roberts, & Jones, 2004) into a reality (Gombolay, Gutierrez, Clarke, Sturla, & Shah, 2015; Sycara & Lewis, 2004). As argued by Tannenbaum and colleagues (2012), teams are increasingly interacting with technology in the form of knowledge repositories, expert databases, forecasting and decision aid tools, and other semi-intelligent information systems that serve as a different form of team member. Eventually, as technology advances, it seems likely that intelligent agents (i.e., robots, avatars) will accompany humans in different types of team settings, but particularly those where a significant risk to human life could be posed (e.g., military, space flight, medical, and emergency response teams). As the role of intelligent agents is changing from tools controlled by humans to being full-fledged team members, capable of dialogue as well as self-initiated autonomous decision making (Zhao, Sinha, Black, & Cassell, 2016), questions arise as to what this implies for group interaction theory. How does human–technology interaction compare with human–human interaction? How are emergent states and processes that are known to be critical to team success in human–human interaction affected by the use of technological tools?

In addition to the advances established in recent years regarding these and other questions (Green, Billinghurst, Chen, & Chase, 2008; Tannenbaum et al., 2012), progress is needed in at least three research areas to leverage the unique strengths of humans and robots to form effective human–robot teams. First, extant research has looked at characteristics (e.g., human-like form, multimodal communication via verbal, vocal, visual, and nonverbal cues) that agents and avatars should possess to evoke social cues and genuine human responses (Astrid, Krämer, Gratch, & Kang, 2010; Green et al., 2008). Currently, agents' capabilities of recognizing and expressing communication cues are rather rudimentary, limited to only a few channels, and certainly not up to par for realizing the transformation of technology as a tool to its role as a team member. Second, more research is needed on how critical team states, such as trust, identity, and shared cognition, are influenced by the introduction of a technological counterpart (Tannenbaum et al., 2012). Although well researched in human–human teams, the examination of these processes and emergent states in human–robot teams is an emerging area of study (e.g., Gombolay et al., 2015; Shah, Wiken, Williams, & Breazeal, 2011). Third, whereas the focus is heavily geared toward making robots more human-like, it seems crucial to carefully contemplate what level of resemblance between humans and robots would be optimal to facilitate effective human–robot teamwork in a particular area (Nunamaker, Derrick, Elkins, Burgoon, & Patton, 2011). Depending on the particular purpose and setting, technology may be designed to play a more authoritative/expert role, and to always take the most optimal/rational decision, or technology may be purposefully designed to be fallible, make mistakes, and be able to learn from them and interact with humans in a more collaborative peer-like way. For example, recent research has evaluated the role of different impression management techniques, such as ingratiation and self-promotion on intelligent agents, and found that these influenced perceptions of trustworthiness, expertise, and power (Derrick & Ligon, 2014).

As human interaction with technology increasingly occurs in small groups within and outside workplaces, the use of technology holds enormous promise to not only assist humans in their tasks but also facilitate acquisition of core competencies, such as literacy, numeracy, as well as socioemotional skills, such as collaboration, curiosity, grit, and leadership (Sheridan, 2016). An important prerequisite for developing such technologies is to better understand how productive and unproductive behaviors unfold in human–human interaction. This understanding can then be used to guide technology design to implement a similar repertoire of human behaviors, to appropriately scaffold the group interaction and achieve desirable socio-cognitive outcomes.

Crucial to group analysis and technology support for group work is the development of perception, reasoning, and generation modules. Specifically, computer scientists and social scientists are interested in how can technologies sense observable behaviors and social states in humans, how can technologies make a decision, and how can technologies respond using verbal and nonverbal behaviors. In addition, it is important to understand how humans perceive, understand, and react to technology, whether used as a sensory input for research or when intelligent agents are part of the team.

In the following, we introduce these modules, with an emphasis on the overarching research question on how to bring together computer scientists and social scientists to synergistically develop theoretical models that would explain and drive research for both fields. Potential research questions are offered.

Perception

At the perception level, computer support capitalizes on the computer scientist’s expertise of discovering patterns and latent variables in multimodal behavior data stream (Vinciarelli et al., 2009), and the social scientist’s expertise of identifying elements of these observable behaviors that are cues to mental states or underlying psychological states (Heylen, 2006). Such a complementary perspective can help to bridge the gap between activity recognition and intent recognition, a fundamental challenge in analysis of human behavior in group work. Activity recognition refers to discretizing a sequence of possibly noisy and intermittent low-level data gathered by physical sensors, such as cameras, wearable sensors, and instrumented user interfaces, to discover and extract interesting patterns in noisy data that can be interpreted as meaningful activities. Intent recognition, on the contrary, is a way of translating noisy, low-level data into models that describe underlying intentions that are interpretable in more abstract terms, and that can be explained to stakeholders and policy makers, providing greater transparency compared with black-box approaches. An important candidate research question is as follows:

> **Research Question:** To perform intent recognition, how can we develop integrated frameworks that allow understanding the communicative (Poggi, 2002) and discourse functions (Fetzer, 2013) that observable verbal and nonverbal behaviors serve?

A unique challenge that pertains to this research question is the many-tomany mapping between a detected activity and the corresponding inferred intent. For example, a smile can index happiness, embarrassment, or condescension depending upon context of the interaction. Furthermore, the conversational intent of a behavior can span propositional (where the behavior contributes to the informational content of the interaction), interactional (where the behavior serves to manage the interaction via turn taking), or interpersonal (where the behavior is used to manage the relationships among group members by indexing coordination, rapport, and positivity) dimensions.

Another opportunity for interdisciplinary research in the field of perception includes building up capabilities of visual and mental perspective taking, something that comes to humans very naturally. This may help close the fundamental perceptual gaps among different minds to facilitate subsequent social interaction, in intelligent agents that are being deployed in group work. Perspective taking a crucial part of teamwork, occurs when group members need to anticipate the actions of one another to decide subsequent course of action. It is essential for identification of shared knowledge (Roschelle & Teasley, 1995), establishment of common ground (Clark & Brennan, 1991), and resolution of referential ambiguity in communication (Brennan, Galati, & Kuhlen, 2010). This information would be beneficial in developing theories that seek to further our understanding of team interactions, when teams are comprised of humans or comprised of humans and technology (intelligent agents). Thus, other candidate research questions that lie at the intersection of perception and reasoning are as follows:

> **Research Question:** How can we differentiate between multiple levels of perspective taking, specifically the cognitive connections level (i.e., I see, I hear, I want) and the representational level (i.e., manipulating representations) (Flavell, Green, & Flavell, 1990)?
>
> **Research Question:** What is the interplay among behavior, action, and meaning? Is it different for teams that include intelligent agents?
>
> **Research Question:** How do individuals infer meaning from behavior and how can we use that information to understand team processes?
>
> **Research Question:** How can models developed in computer science inform knowledge about meaning inferences?

Reasoning

At the reasoning level, developing schemata of behavioral understanding and intelligence that makes the interaction social (Breazeal, 2004) is a fundamental capability required for a technology to cooperate, coordinate, and learn about the shared environment (Carley & Newell, 1994; Cassell et al., 1999). In this regard, insights from human–human interaction are a rich source of information for interdisciplinary development (e.g., Shah et al., 2011). Simply put, this involves inferring what individuals are doing in a group interaction, why they are doing it, and what will they do next—not only along the task dimension but also along the relational dimension of the interaction. Technically, this can be understood as recognizing causality or temporal ordering in the relationships between a set of discovered activities across multiple individuals. Researchers are just beginning to scratch the surface along these directions (Zhao et al., 2016).

Our understanding of how team members develop representations of behaviors based on their perceptions and interpretations of information is limited. When faced with an incoming stream of sensory data, a technology must figure out which of these are relevant to the task at hand. This is an important capability for generating coherent behavior as well as for learning, given that the search becomes larger as perceptual abilities and complexity of the environment increase. In addition, gaining a better understanding of how information is combined to create individual and shared understanding is also important and information gleaned from computer science models and input may be beneficial. From here, a number of candidate research questions emerge:

> **Research Question:** How can we assemble information about decisionmaking models based on humans that can be used by computers (intelligent agents)?
>
> **Research Question:** What models of decision making, inferences, and reasoning are used by teams, and how are they influenced by team structure and team composition?
>
> **Research Question:** How can we leverage our understanding of team interactions and reasoning in the development of intelligent agents?

Generation

With regard to generation, it is important to understand how behavior is enacted. Theory of mind has been suggested as one way in which individuals use their knowledge and thoughts to then engage in specific behaviors (Goldman, 2012). Computationally developing behavioral models for individuals within teams or teams as a whole, especially when teams are comprised of both human and machines (Breazeal, 2009; Cassell et al., 1994), is a ripe area of interdisciplinary research. It is challenging because of the following reason.

While a machine's theory of mind is likely to be carefully engineered with, as a starting point, a model of human behavior and psychology (with some level of fidelity) and the ability to learn from experience, humans, in contrast, are likely to have no theory of mind for the machine. Of course, humans have a tendency to anthropomorphize (see Torrey, Fussell, & Kiesler, 2009), and so they might also quickly assume some theory of mind for their machines, which is very likely to be inaccurate. This will matter, because, if the machine is perceived to behave as if it has intentionality and artificial empathy (i.e., it is more human-like), humans will defer more task responsibility to it. If the machine acts/reacts in an unexpected way, humans will be much more disconcerted than when they interact with machines without agency (e.g., washing machine) that behave in unexpected ways. The dilemma would then be whether the human fixes the machine, interacts with it in an effort to adjust its behavior, or modifies own expectations for its sake (Dillenbourg, Lemaignan, Sangin, Nova, & Molinari, 2016; Winfield, 2010). Thus, these candidate research questions are posed:

> **Research Question:** How can computational models be developed to understand individual behaviors within a team, collective team behaviors, and the relationship of these to generate appropriately targeted behaviors?
>
> **Research Question:** How can we embed sensory and motor capabilities in technology support for group work to positively affect social behavior?
>
> **Research Question:** How can we augment our theoretical understanding of dynamic team behavior using these sensory and motor capabilities?

Dynamics

An aspect which is transversal to perception, reasoning, and generation is their dynamics, or the study of the time development of these three components. In the framework of groups, this means, for example, to study how the behavior of a single individual evolves over time as an effect of the individual belonging to a group, or how the behavior of the whole group considered as a single entity changes over time as an effect of the social interaction between the members of the group. Pioneering studies are emerging that use computational models for describing social dynamics. For example, several computational techniques were applied to analyze coordinated group activity in terms of interpersonal synchrony and its variation over time (Delaherche et al., 2012). Techniques range from cross-correlation, recurrence quantification analysis (e.g., Marwan, Romano, Thiel, & Kurths, 2007), and causality (Granger, 1969) for the analysis of continuous time-series data to methods based on event synchronization (Quian Quiroga, Kreuz, & Grassberger, 2002) and cross-recurrence analysis for analysis of categorical time-series data (see Coco & Dale, 2014, for an R package devoted to that).

Another example is an analysis of functional roles. Sanchez-Cortes, Aran, Mast, and Gatica-Perez (2012) used four different computational approaches to infer the emergent leader in a small group meeting by combining acoustic and visual features. Approaches include a rule-based one, a rank-level fusion, which extends the rule-based approach, a support-vector machine, and a collective classification approach. Best results were obtained with collective classification. Varni, Volpe, and Mazzarino (2011) applied graph models to describe the temporal evolution of leadership in a small group of people asked to dance together. Nodes in the graph represented the participants and edges were weighted so that they represented the extent at which one participant anticipates the movement of another one. These computational models can then be combined with our theoretical knowledge from social science to augment our theoretical (and empirical) understanding.

Despite these initial efforts, many research challenges still remain. For example, computational studies are not yet comprehensively grounded in well-established social science theories. Dynamics at different timescales, ranging from short temporal intervals in a range of 0.5 to 3 s (Fraisse, 1963; Pöppel, 1997), to the duration of one session (e.g., a meeting), to very longterm dynamics (i.e., how belonging to a group changes one's behavior through a series of subtle shifts happening over months or even years), still have to be addressed. Provided that the phenomena we are interested in are better modeled not just as static states but rather as dynamic processes, a candidate research question is offered:

> **Research Question:** How can we develop quantitative models and computational approaches to analyze and model dynamics at both the perceptual level and at the cognitive level, and to use this information to drive the generation component over time?

Unit of Analysis

Finally, the level of analysis in studying group phenomena poses an interesting opportunity for interdisciplinary research. Investigating group processes requires the use of research designs and analytic strategies that recognize the interdependence of social behavior (Kashy & Kenny, 2000). So far, much of the research in computer science has focused on studying dyads rather than groups, simply to constrain the complexity of behaviors to be analyzed. Evidently, studying dyadic relationships can reveal important things about groups. Many phenomena can occur in both dyads and groups, and research on dyads can sometimes help to understand groups better. However, studying dyads as if they are groups has serious limitations.

According to Moreland et al. (1996), there are at least four reasons why an exclusive focus on dyads would be disadvantageous for truly understanding group phenomenon. First, there are phenomena that can occur in groups, but cannot occur in dyads, simply because dyads are too small. Dyads, for example, cannot form coalitions, have no newcomers or old-timers, nor can there be majority/minority influence in dyads. Hence, in studying dyads, we would be unlikely to learn much about these phenomena. Second, some phenomena appear to occur in both dyads and groups but operate in fundamentally different ways in groups, mostly because they are more complicated in groups, such as negotiation and conflict (argument). Studying only dyads, then, could produce pseudo-knowledge about how those phenomena operate in groups. Third, Moreland warned against studying dyads within a group context, without considering the possibility that other group members may influence the behavior of both the dyad and the group. By not acknowledging the social context in which some dyadic relations occur, the impact of the social context cannot be well understood. Finally, Moreland warned against studying groups as if they were nothing but collection of dyads, for example, by decomposing groups into all the dyads that they contain and then consider those dyads separately from one another.

Evidently, the complexity of group dynamics and contexts in which they evolve is considerably large, simply due to the variability in group size. It is important that social scientists and computer scientists work together to find ways to resolve the tension between preserving enough complexity in the model to obtain valid scientific insight while attaining computational feasibility. This involves search of the space of possible representations of the data so that contextual information is retained to some extent and also making sure that those behavioral representations are learnable by ML algorithmic approaches. Technically, the input feature space should be sufficiently expressive for an ML model to find characteristics that exemplify each category and distinguish it from other categories. Thus, this final candidate research question is offered:

> **Research Question:** How do we decide whether to treat the group as a context and analyze the effects on the individual, or analyze the group phenomena and treat the individuals as contributors to the group processes? Are there specific decision rules or heuristics that we can identify?

Conclusion

In this article, we, a team of authors from many disciplines, have attempted to describe the state of current theories and theoretical thinking in social science and computer science regarding teams and teamwork. We have further attempted to connect and identify the relationships between these theoretical approaches and models, and to specifically identify gaps in our understanding in which theories can and should be integrated, and offer some candidate research questions that are best addressed by integrating theoretical models from computer science and social science.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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