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Building Intelligent Tutoring Systems for Teams

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MACROCOGNITION IN TEAMS AND METACOGNITION: DEVELOPING INSTRUCTIONAL STRATEGIES FOR COMPLEX COLLABORATIVE PROBLEM SOLVING

Olivia B. Newton, Travis J. Wiltshire and
Stephen M. Fiore

ABSTRACT

Team cognition research continues to evolve as the need for understanding and improving complex problem solving itself grows. Complex problem solving requires members to engage in a number of complicated collaborative processes to generate solutions. This chapter illustrates how the Macro cognition in Teams model, developed to guide research on these processes, can be utilized to propose how intelligent tutoring systems (ITSs) could be developed to train collaborative problem solving. Metacognitive prompting, based upon macrocognitive processes, was offered as an intervention to scaffold learning these complex processes. Our objective is to provide a theoretically grounded approach for linking intelligent tutoring research and development with team cognition. In this way, team members are more likely to learn how to identify and integrate relevant knowledge, as well as plan, monitor, and reflect on their problem-solving performance as it evolves. We argue that ITSs that utilize metacognitive prompting that promotes team planning during the preparation

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stage, team knowledge building during the execution stage, and team reflexivity and team knowledge sharing interventions during the reflection stage can improve collaborative problem solving.

Keywords: Macro cognition; team cognition; metacognition; problem solving; collaboration

Theorizing out of the cognitive sciences suggests that cognition and environment are a coupled system within which performance occurs (Fiore, Rosen, Salas, Burke, & Jentsch, 2008; Li, Clark, & Winchester, 2010). The physical and cognitive elements of the system are inseparable and a social system is overlaid upon that (Fiore, 2013; Suchman, 1993). Further, both the organism within that system and environment itself operate through this interaction (Fiore, Rosen, et al., 2010). Through a process of co-emergence, the system adapts because of the interaction (Wiltshire, Butner, & Fiore, 2017). Team cognition, then, can be seen as a process whereby a system is adapting through coupled interaction between organism and environment affecting each other (Fiore & Salas, 2004). Philosophically, then, the system does not merely process information, the system produces meaning via interaction in that system (Li et al., 2010).

We open with this broad philosophical perspective to make the point that cognition is not just something that happens in the head. Rather, team cognition occurs through a coupling of team members with their task environment. In service of problem solving, it necessitates interaction with their environment and with each other. Further, given that the vast majority of problems do not have only a single solution, team members must create solutions and choose among them. As such, team cognition requires navigating this environment; it requires interaction that operates within, and chooses among, a space of possibilities, while creating and coordinating knowledge through interacting team members. This is a complex iterative process in that it requires monitoring and regulation of collaborative cognition. In particular, Fiore and Salas (2004) argued that the critical aspect of teamwork is the synchronization of teamwork behaviors, which is driven by shared and complementary knowledge across the team, as well as team member awareness of this distribution. They suggested that team cognition can be conceptualized as the mechanism which “fuses the multiple inputs of a team into its own functional entity” (p. 237). Essentially, they argued that the affective, behavioral, and cognitive processes within the team must effectively bind to produce coordinated teamwork (Fiore & Salas, 2006).

In elaboration of this, when discussing the relation between team cognition and team coordination, Elias and Fiore (2012) noted that team cognition helps to both manage collaborative dynamics and effectively scaffold team interaction. Theoretically, coordination acts as a set of constraints that “endows behavior with meaning and purpose, with directedness and aim, and allows for

anticipation precisely by narrowing the range of action” (p. 585). In short, team cognition encompasses the ways in which a team sequences and times their behaviors to achieve effective performance (Elias & Fiore, 2012; Fiore, Salas, Cuevas, & Bowers, 2003; Rosen, Fiore, Salas, Letsky, & Warner, 2008). Indeed, an important meta-analysis showed that team cognition broadly predicts the task-related processes of the team, the teams’ motivational states, as well as the performance of the team (DeChurch & Mesmer-Magnus, 2010).

An understanding of team cognition for the purposes of intelligent tutoring is advantageous and complementary to the study of individual cognition because with a team comes a suite of collective cognitive resources including knowledge, skills, and abilities all of which are necessary for accomplishing complex tasks (Rico, Sánchez-Manzanares, Gil, & Gibson, 2008; Sikorski, Johnson, & Ruscher, 2012). Much like individual cognition, team cognition, occurring at the level of the team, extends beyond more than just internal knowledge. It also includes team cognitive processes such as collaborative problem solving, decision making, and planning (Cooke, Gorman, Myers, & Duran, 2013; Fiore, Rosen, et al., 2010). For the purposes of our chapter, we define *team cognition* as an emergent phenomenon that arises in the dynamic interdependency of inter-individual and intra-individual factors as team members interact with their environment, their technology, and each other (Cooke et al., 2013; Fiore & Schooler, 2004; Rosen et al., 2008).

With this as our stepping off point, we now draw from a specific team cognition theory that is built out of this perspective. The Macro cognition in Teams model (MITM) is a theory of collaborative problem solving that unites concepts and methods from a variety of disciplines that have studied groups and teams. It is based upon a synthesis of disciplines across multiple domains, ranging from the psychological and organizational sciences to computer science, cognitive science, and human factors. Building and synthesizing from earlier work on team problem solving (Fiore & Schooler, 2001, 2004; Zhang, 1997), team cognition (Salas & Fiore, 2004; Salas, Fiore, & Letsky, 2012), and distributed cognition (Hutchins, 1995a, 1995b), the MITM is positioned within the broader literature on shared cognition. From this, the MITM integrates into a concise theory, an approach for examining complex forms of collaborative cognition. Our goal with this chapter is to add to the developing literature on intelligent tutoring for teams (Fletcher & Sottilare, 2017; Gilbert et al., 2017; Sottilare et al., 2017). We show how the MITM is well suited as a foundation for integrating complex collaborative cognitive processes with intelligent tutoring systems (ITSs).

MACROCOGNITION IN TEAMS MODEL

The MITM integrates a set of theoretical elements in order to capture the iterative processes unfolding during collaborative cognition (for an in-depth

discussion, see: Fiore, Elias, Salas, Warner, & Letsky, 2010; Fiore et al., 2008; Fiore, Rosen, et al., 2010; Fiore, Smith-Jentsch, Salas, Warner, & Letsky, 2010). First, it is multi-level in that it encompasses individual and team level factors. Second, it addresses internalized and externalized cognitive functions. Finally, it incorporates temporal characteristics to examine phases of collaboration and how these alter process and performance. The model consists of five overarching components that describe processes engaged by a team when collaborating in complex contexts. The MITM additionally includes a detailed delineation of the candidate measures and metrics that can be used to assess the processes arising during collaboration (Fiore, Smith-Jentsch, et al., 2010). Finally, because the MITM focuses on how teams build knowledge, it provides a means for conceptualizing how teams transform data to information to knowledge (Fiore, Smith-Jentsch, et al., 2010). Given its emphasis on knowledge building, we suggest that these provide descriptions of, and targets for, the processes foundational to intelligent tutoring. In this section, we first provide brief summaries of the major components of the model, and then summarize some of the empirical work that has been based upon the MITM model.

We start with *Internalized Team Knowledge*. This refers to the knowledge held by each individual team member and is the knowledge associated with shared cognition (i.e., components of a shared mental model and/or a transactive memory system). Note, though, that this could be knowledge not yet shared on the team level. This could encompass specialized knowledge about organizational processes, resources, or systems managed by that team member. It can also include their knowledge about fellow team members (e.g., skills, responsibilities, roles). We then consider *Individual Knowledge Building*. This refers to processes involved in expanding one's own knowledge base when engaged in work. These are actions taken by an individual team member for their idiosyncratic purposes of finding out more about the situation they are addressing. This, in turn, may feed into collaboration processes occurring at a later time. Next is *Team Knowledge Building*, which describes team member processes engaged to develop actionable knowledge related to the context on which they are working. This, for example, can contribute to teams adding to, or sometimes developing, their shared mental models or shared problem models (Fiore & Schooler, 2004).

Just as critical, though, is *Externalized Team Knowledge*. This describes knowledge shared by the team. Externalization is meant to capture how knowledge is communicated (e.g., verbally or with artifacts) in order to take what is internally held and then distributed across members of the team. This is used to capture how team members develop shared understanding of their situation (e.g., task, goals, problem), and whether they are considering similar processes for addressing their problem. In brief, externalization is the means through which the team understands how their knowledge is shared and/or complementary (Fiore & Wiltshire, 2016). Last, *Team Problem Solving Outcomes* describes the products of the collaboration, that is, the notional solutions generated by

the team to meet the problem-solving objective. Depending upon the situation, these might be revised dependent upon the degree of success/failure in meeting objectives. Further, from these, we can understand the efficiency of the team in coming up with their proposed outcome (e.g., plan, product), and the efficiency in resources and time needed to actually execute whatever is the proposed outcome.

Within each of these major macrocognitive components are a subset of processes. These are engaged individually and collaboratively as the team works through their situation. We suggest that the explication of these collaboration processes can contribute, in new ways, to intelligent tutoring research. More specifically, these sub-processes can be targets for learning and training when considered in the context of processes engaged by members of a problem-solving team. We will provide more detail on these in a later section focused on how ITSs can prompt team cognitive processes. We next turn to a brief overview of how the MITM model has been examined in a number of empirical settings.

Empirical Base for MITM

Given the detailed account of collaborative cognition provided by the MITM (Fiore, Smith-Jentsch, et al., 2010), researchers from a variety of domains have used it to examine the processes teams employ when engaged in complex work settings. Such studies have used the MITM framework to study complex problem solving so that the processes and functions occurring during the problem solving can be demarcated. Said another way, the MITM has supported the examination of complex problem by providing a level of abstraction capable of capturing collaboration processes critical to team cognition.

Some have examined team cognition in the context of synthetic task environments. For example, expert teams experienced in air operations centers were studied to better understand their collaborative processes (Hutchins & Kendall, 2010). This study found that the majority of collaborative processes consisted of individual information gathering and team information exchange. This was followed by individual information synthesis and team knowledge sharing. These results point to the importance of team information exchange and knowledge sharing for the development and maintenance of team knowledge structures. Further, these findings suggest that team knowledge building is followed by a “decision to take action” and that such actions result in a need to update knowledge structures based on the emergence of novel information about the current situation. This sequence can, and arguably must, occur iteratively for the successful completion of a collaborative problem-solving task.

Others have examined elements of the MITM in laboratory studies requiring teams to analyze and write a report regarding a fictitious information systems company (Seeber, Maier, & Weber, 2013). Here, they were able to use the

MITM model to analyze differences in the flow of team collaboration activities. For example, they find that larger differences occur in the team knowledge building function having to do with how ideas are evaluated and negotiated. These differences are reflective of the team's solution-minded behavior. Viewing this in the context of problem-solving theory more generally, the MITM was able to show how a team's ability to effectively shift between divergent and convergent thinking, following a period of idea generation, can influence the quality of the decisions made by the team.

The MITM has also been used to study collaborative cognition in complex real world problems through the use of retrospective analyses of coded transcripts and chat logs. This included study of the North American Aerospace Defense Command with transcripts of their responding to aircraft hijackings on September 11, 2001, as well as Maritime Interdiction Operations conducted by the US Coast Guard when boarding a ship suspected of carrying contraband (Hutchins & Kendall, 2010a). In this work, individuals engaged primarily in information gathering and information synthesis while the team communications consisted primarily of knowledge sharing. The MITM model was also used to frame an analysis of communications of responders in Port-au-Prince to the Haiti earthquake in 2010 so as to understand cognition in the context of collaborative information exchanges (Hutchins, 2011). This study found very similar results when looking across responders addressing water needs and medical issues, with the majority of communications focusing on team information exchange.

Most recently, the MITM was adapted for the study of collaborative problem solving at NASA's Johnson Space Center (Fiore, Wiltshire, Oglesby, O'Keefe, & Salas, 2014). NASA's Mission Control Center (MCC) is responsible for control of the International Space Station (ISS) and responds to problems that obstruct the functioning of the ISS. These problems are often complex, requiring individuals and teams to work collaboratively. The MITM was used to study the types of problems experienced by the MCC, and examine individual and collaborative problem solving with a focus on how Mission Control personnel – each with their own skills and responsibilities – exchange information to gain a shared understanding of the problem. Here, knowledge building resulted from the interplay of internalized knowledge (e.g., rules, system functions), and externalized knowledge (e.g., collaboratively generated situation updates). Learning “about” this problem led to the creation of new knowledge; specifically, collaborative learning processes led to a solution requiring implementation from multiple teams at mission control (Fiore et al., 2014).

Based upon the detailed description of collaborative processes outlined in the MITM, it has also been used as a means for technology development. For example, Seeber and colleagues (2013) created software to help study interactions within the team during collaborative problem solving. Their Collaboration Process Analysis (CoPrA) tool captures temporal and phasic aspects of team process. The CoPrA tool provides insight into a team's

collaborative processes through an analysis that enumerates and visualizes the sequence of actions by each member of the team over time. This demonstrates how the MITM can be integrated with existing methods to develop new technologies aimed at capturing and identifying the collaboration patterns of a team.

The MITM has also been used to study how organizations develop business process models in teams with members who are often not collocated as well as how to develop technologies that help to record and analyze collaboration during process modeling (Forster, 2013; Forster, Pingera, & Weber, 2013). This work also used visualization of communication and action between team members, both as a means for understanding the collaborative process and for improving a team's ability to effectively transition through different collaboration phases of a project.

More recent work has used the MITM to focus on emergent and dynamic processes arising from collaboration. This has been done in the context of collaborative problem solving to study phase transitions in problem solving using the processes and phases identified in the MITM (Kitchin & Baber, 2017; Wiltshire et al., 2017). Drawing from dynamical systems theory, this work suggests that team communication can serve as a basis for identifying phase transitions in complex collaborative problem solving, where phase transitions are used to describe a meaningful change in the team's coordination behavior. Such phase transitions were linked to the MITM and were reflected in the team's entropy level, quantifiable through the team's communication patterns. Specifically, an algorithm was used to calculate the level of entropy at a given point in time based on the team's corresponding communication sequences. These communication sequences were coded following the MITM such that the processes engaged by teams during problem solving could be clearly demarcated. Communication sequences exhibiting a high level of entropy indicate a shift in a team's coordination pattern. Importantly, these peaks in entropy can be indicative of both the team's stability and flexibility, and, in turn, their problem-solving performance (Kitchin & Baber, 2017; Wiltshire et al., 2017). Previous research suggests that this technique can be used as an unobtrusive measure of constructs related to team knowledge building (e.g., distributed situation awareness).

Others have used MITM to develop computational models in agent-based simulations that examine the generative processes driving knowledge emergence in teams (Grand, Braun, Kuljanin, Kozlowski, & Chao, 2016). In these models, team members are represented by agents, and these agents interact with each other over time, processing and sharing information in a task environment. The resultant simulations have both explanatory and prescriptive purposes, and researchers have manipulated both individual (e.g., communication, information processing skills) and environmental features (information in the environment that requires or does not require specific expertise). Findings show that individual attributes of team members can influence team knowledge building

and that a lack of effective coordination with respect to communication can stifle important information sharing among team members.

Similar research has used the MITM as a foundation for modeling multilevel dynamics in learning and performance within teams (Bell, Kozlowski, & Blawath, 2012; Kozlowski, 2015; Kozlowski & Bell, in press; Kozlowski & Chao, 2012; Kozlowski, Chao, Grand, Braun, & Kuljanin, 2016). The extant literature notes that much research examining team processes has failed to capture the dynamic nature of the phenomena. Instead, related work frequently employs static measures of performance outcomes. This is, in part, due to the lack of unobtrusive measures and other methodological challenges. For instance, different operational environments may exhibit differing rates of change in team process and thus require differing rates of measurement to capture important shifts or emergent phenomena. This work also points to the value of the multilevel approach of MITM, which delineates the process by which interactions between team members and their environment lead to the emergence of individual and team knowledge. While laboratory studies have struggled to capture these emergent phenomena, advances in technology and computational modeling of social dynamics, like the aforementioned agent-based simulations, may help bridge the gap in understanding and investigating the dynamics of collaborative problem solving (Kozlowski et al., 2016).

In sum, the MITM has been used to study team cognition in complex collaborative problem solving and decision making in a variety of contexts both in the laboratory and in the real world. The MITM set out to address an important challenge for understanding collaboration – that of describing the team cognitive processes driving knowledge building when teams are working on complex real world tasks. Further, it has described the inter-relationships in collaboration processes that emerge in such settings in order to help develop a multilevel theoretical understanding of team performance. This yields a more sophisticated understanding of how team cognitive constructs cross levels. Through this, it provides explanatory power when trying to diagnose the causal factors associated with team performance. The MITM discusses the kinds of processes engaged by teams that we suggest are adaptable for use in ITSs. To provide conceptual grounding for how the MITM model can be adapted for research on intelligent tutoring, in the next section we discuss a critical component of this, that of communication analyses and automated, or semi-automated methods for parsing communications within the team. These provide the necessary foundation from which to build ITSs that can provide instructional strategies for team cognition.

Communication Analysis in Complex Problem Solving

An ITS can capitalize on team communications as a means of identifying learner and team states. In the ITS, team communication is a source for learner

data and this data can serve as an indicator for the adaptive selection of an appropriate instructional strategy. Past work describes exactly how the analysis of communication sequences can be used to classify team performance levels through the identification of patterns, frequencies, and content in communication between team members. Until recently, research in this domain often relied on the manual coding and analysis of communication to extract meaningful results. The advent of new technology and progress made in natural language processing capabilities means that these types of analyses can be automated (Foltz & Martin, 2008; Murase, Carter, DeChurch, & Marks, 2014). Current efforts in this domain include the development of methods and technology to capture, aggregate, and analyze communications as indicators of team cognitive states in real-time operations (Driskell, Burke, Driskell, Salas, & Neuberger, 2014; Driskell, Driskell, & Salas, 2017).

Over the last two decades, several methodologies have been proposed for the analysis of communication data in teams. Latent semantic analysis (LSA), an increasingly popular computational approach, automates communication analysis and calculates several metrics used to assess the various aspects of team collaboration including coordination behavior related to information sharing and knowledge building (Gorman, Foltz, Kiekel, Martin, & Cooke, 2003). Other researchers have proposed somewhat similar approaches aimed at classifying communication sequences based on their meaning and relevance to the task at hand (Entin & Entin, 2001; Fischer, McDonnell, & Orasanu, 2007; Kalia, Buchler, DeCostanza, & Singh, 2017). Researchers have elaborated on differences in task-related communication, integrating past work to generate a set of five generic classes of communications (questions, directives, requests, commissives, and informatives) and corresponding dyadic elements in communication sequences (i.e., responses to statements belonging to one of the five classes; Kalia et al., 2017). These generic classes are derived from classifications described in the extant literature and are applicable across a variety of task domains for the assessment of collaborative processes. Related work shows that team knowledge building is more effective in teams where all members actively engage in information sharing compared to teams where only a small number of members share information (Grand et al., 2016). Indeed, past empirical research in team communication has found that the distribution of communication across team members influences team knowledge building (Foltz & Martin, 2008).

Team communication analyses can also be conducted with the intent of classifying and quantifying communication breakdowns as measures of team knowledge structures (e.g., SMM similarity; Bearman, Paletz, Orasanu, & Thomas, 2010). This involves classifying communication sequences as belonging to one of three categories: operational, informational, and evaluative. Classification techniques have also been used to score team performance and assess the quality of collaboration in a team (Bonner et al., 2017; Foltz & Martin, 2008; Rosen & Foltz, 2014). These classifications can be used to identify communication patterns between and within teams. For instance, high-performing teams have been

found to more frequently use task-related communication compared to low-performing teams (Foltz & Martin, 2008). However, these findings are limited with respect to their generalizability as communication frequency itself has been found to vary depending on the workload and expertise of the team.

More relevant to ITSs, a recent study showed how participants can use predefined messages to communicate with either a human or software agent teammate as they worked together to solve problems in a computer-based assessment of collaborative problem-solving skills. The results of this study indicate that computer agents can augment an individual's collaborative skills (Rosen & Foltz, 2014). More specifically, this is an important proof-of-concept for conceptualizing how ITSs can be developed in support of complex problem solving. Because the agent itself is endowed with a comprehensive set of collaborative problem-solving skills, and can monitor the human teammate, this not only expands the possible collaboration space for the problem-solving task, it also suggests a route for instructional intervention. In brief, while this study made use of predefined messages which ultimately constrained communication between teammates, it did provide evidence for the beneficial effect of agent collaborators and allowed for standardization and automation of scoring (Rosen & Foltz, 2014).

In sum, team communication is a powerful means through which to understand individual and team cognitive states across various task domains (Cooke et al., 2013; Cooke, Salas, Kiekel, & Bell, 2004; Poole, 1997). We suggest that the combination of advances in computational linguistics with the rich empirical and theoretical foundation of communication theory in collaborative cognition enables a capability for identifying and developing effective intervention strategies for teams engaged in collaborative problem-solving tasks. With this as foundation, we turn now to discussion of how monitoring and regulator processes, that is "team metacognition," can be used in ITSs in service of learning collaborative problem-solving processes.

METACOGNITIVE PROMPTING IN ITSs IN SUPPORT OF COLLABORATIVE PROBLEM-SOLVING TRAINING

Our overarching point is that metacognitive prompts, as an intervention strategy, can support collaborative problem solving in an ITS. Past work describes how metacognitive prompts can be used to promote knowledge building to improve overall learning and problem-solving outcomes (Fiore & Vogel-Walcutt, 2010; Wiltshire, Rosch, Fiorella, & Fiore, 2014). Yet little work has specifically integrated complex problem solving, metacognition, and intelligent tutoring.

In this section, we redress this gap by outlining how the MITM can be leveraged to guide the development of metacognitive prompting for use in ITSs.

In the following subsections, we sketch out guidelines that serve as markers for incorporating specific forms of prompting. These, in turn, can be used to test variations of prompting to determine their efficacy in improving learning. Next, we provide an overview of metacognition theory and research to scaffold our discussion of how to connect this to ITSs and collaborative problem solving. Then we briefly discuss how methods used in ITSs, such as communication analyses and conversational agents, can be used in support of team cognition training. We then detail specific guidelines for metacognitive prompting that are built off of the MITM.

Metacognition Theory and Research

Metacognition is the awareness of one's own cognitive processes and the ability to consciously monitor and control these processes (Schraw, 1998; Favell, 1979). Metacognitive ability has been shown to be beneficial for a variety of task contexts such as problem solving (Fiore, Cuevas, Scielzo, & Salas, 2002). For example, prior research showed that metacognitive prompting, such as generic question stems or diagrams with content-free prompts, can facilitate learning (Cuevas & Fiore, 2014; Cuevas, Fiore, & Oser, 2002). Further, recent meta-analyses document how metacognition leads to superior learning outcomes in the workplace as well as in the classroom (Dignath & Büttner, 2008; Sitzmann & Ely, 2011).

Metacognitive processes contribute to learning in a variety of ways and can depend on the stages of learning. To elaborate on this, Fiore and Vogel-Walcutt (2010) developed the concept of a training cycle to differentiate metacognition processes as they occur across a "training cycle." This cycle encompasses preparation for, execution of, and reflection upon, learning. For example, in a training session, this would cover activities before learning takes place, during the learning stage, and following the learning stage.

The theoretical framework of a "training cycle" was developed to systematically capture the variety of methods/findings examined in the training literature. Specifically, depending on the task, participants may be better able to apply new knowledge to solve novel problems when providing prompting during training as opposed to before or after and this also decreases cognitive load (Fiorella & Vogel-Walcutt, 2011; Vogel-Walcutt, Fiore, Bowers, & Nicholson, 2009). In other settings, metacognitive prompting before or after training will foster learning (Fiore, Johnston, & Van Duyne, 2004; Smith-Jentsch, Zeisig, Acton, & McPherson, 1998; Vogel-Walcutt et al., 2009). Fiore and colleagues' training cycle takes into account the different stages of learning one experiences when engaged in training. Specifically, they consider preparatory stages of learning as the kinds of pre-task behaviors, like planning, that serve as a means of setting up the learner for early expectation about the task. Next, they include execution stages of learning, which involves activities that address performance

while one is engaged with a training task. Finally, the reflection stage involves some form of feedback and/or post-task analysis of performance after finishing the training (e.g., to recognize errors).

The purpose of delineating these stages of learning and training is to more precisely guide the type of instructional strategy that is most effective at maximizing learning (i.e., before the task, during the task, or after the completion of the task). This overview serves as a primer for how metacognitive prompting can be conceptualized for testing variations of intelligent tutoring in service of training collaborative problem solving. That is, although metacognitive prompting is traditionally studied for knowledge acquisition (Fiorella & Mayer, 2012; Fiorella, Vogel-Walcutt, & Fiore, 2012), our focus is its application to collaborative problem solving. Building off the work of Wiltshire, Neville, Lauth, Rinkinen, and Ramirez (2014), we suggest that metacognitive prompting that is systematically integrated into an ITS, and differentiated across the three stages of the training cycle, can serve as a potent learning intervention to improve collaborative problem solving. Our overall argument is that ITSs should study how to integrate planning, execution, and reflection-based metacognitive prompts to improve collaborative problem-solving processes. The necessary precursor for this, though, is an automated capability for communication as it occurs in training settings. That is, for ITSs to introduce metacognitive prompting based on the MITM, it must have some natural language capability to interact with team members. We next describe a subset of the research that documents the feasibility of automated communication analyses to document the viability of our primary claims.

Communication and Conversational Agents in ITSs

For the purposes of intelligent tutoring, automated communication analyses create the capability for conversational agents as team members. These, in turn, can provide a team of learners with metacognitive prompts aimed at supporting collaborative problem-solving skills. Recent work shows that conversational agents can facilitate learning processes by guiding learners through their reasoning in a tutoring session (Dyke, Adamson, Howley, & Rosé, 2012). For example, research based on the Academically Productive Talk (APT) methodology, which stresses the importance of social interaction in supporting learning processes, has shown that interventions can scaffold learning and performance. In particular, agents used in these studies were designed to facilitate APT by means of generating novel dialog and scaffolding the interactions that produce such dialogs (Adamson, Ashe, Jang, Yaron, & Rosé, 2013; Dyke et al., 2012). To do this, the agent might offer an individual learner a prompt via a chat log that directs them to contribute to an ongoing discussion. Based on previous work with human teachers, computer agents guided learners through their tasks

and facilitated discussion through the use of several techniques. This included asking learners to state another learner's reasoning in their own words, offer their opinion on another learner's reasoning, and provide additional support for their own line of reasoning. The results of this work show that conversational agents can indeed produce a beneficial effect on individual and collaborative learning in computer-based training (Ferschke et al., 2015). Furthermore, recent research finds that conversational agents increased information sharing between members of a group in computer-based collaborative learning (Adamson et al., 2013).

In the context of intelligent tutoring, we suggest that real-time lexical analysis can be used to identify sub-optimal learner and team states through the classification of communication patterns exhibited by the team. The observed patterns can serve as indicators for specific intervention strategies based in metacognitive prompting. To do this, the ITS must have adequate natural language processing capabilities in order to capture and classify communication in real-time. Communication among team members can thus serve as a source for learner data through the course of a tutoring session.

We suggest that this body of work serves as a proof of concept for communication analysis techniques from which to analyze data, and classify learner and team states as optimal or sub-optimal, as they relate to collaborative problem-solving skills. Further, this allows for the introduction of metacognitive processes into the collaborative problem-solving context. As noted earlier, effective teams engage in monitoring and regulation of their collaborative processes. Given this, we argue that, by linking this to the MITM, we can guide ITS research such that it studies how to augment these processes in service of improving team cognition. As such, we next discuss how to leverage these technological advancements for using metacognitive prompting in service of instruction in collaborative problem solving.

Metacognitive Prompting during the Preparation Stage

Activities during preparation include the kinds of team cognitive processes that create initial expectations for the learning context (e.g., planning). During this stage, metacognition could involve preparatory questions that require team members to speculate about critical task elements they will be facing and/or self-assess their capabilities in anticipation of the operational context they will be facing (Klein, 2008; Veinott, Klein, & Wiggins, 2010). We suggest that metacognitive prompts focusing on team planning macrocognitive processes are ideally suited for testing in ITSs. Team planning has been found to improve team performance prior to mission execution (Cooke et al., 2013) and includes goal setting, role clarification, task prioritization, as well as the assessment of information required by team members dependent upon their role and how members

Table 1. Representative ITS Prompts Guiding Metacognition during the Preparation Stage of the Training Cycle.

<ul style="list-style-type: none">• What are your goals as a team for the upcoming performance episode?• What is your plan for accomplishing these goals?• What roles will each of you play?• What types of tasks are of priority and which ones are of less importance to your goals?• During the mission, what types of information do all team members require access to and which types are only required by specific team members?• What are the likely issues that can arise with the current plan?• How do you intend to back each other up in the event of errors or issues with the plan?
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will address errors (Hackman, Brousseau, & Weiss, 1976; Stout, Cannon-Bowers, Salas, & Milanovich, 1999). This can include, for example, deliberate and contingency planning to support a team’s ability to deal with routine and non-routine events (Marks, Mathieu, & Zaccaro, 2001). Studies show that approaches like reactive strategy adjustment planning improve overall performance by supporting coordination within the team (DeChurch & Haas, 2008). Given this, we provide the following guideline for ITS research and representative metacognitive prompts for the preparatory stage (Table 1).

- *ITS Guideline 1.* ITS research can integrate metacognitive prompting based upon macrocognitive processes such as planning during the preparation stage to determine how this alters collaborative problem solving during the execution stage.

Metacognitive Prompting during the Execution Stage

Activities during execution include the kinds of team cognitive processes that focus the attention of team members on monitoring and regulatory behaviors. Metacognitive prompting in this case might include questions driving self-assessments. For example, these would help teams assess the degree to which they clearly understand their task approach, whether they are meeting goals, or if they need to modify strategies (cf. Fiorella et al., 2012). Further, these could more generally guide the macrocognitive processes of team knowledge building and sharing. Specifically, problem-solving teams often have individuals with unique forms of knowledge requiring integration to effectively meet goals (Fiore, 2008). The challenge for problem-solving teams is overcoming knowledge sharing barriers (e.g., discussing only commonly held information). Studies show that knowledge building training which focuses on schema-enriched communication (SEC) to elicit the organization of team member knowledge and their assumptions about such knowledge and associated interpretations of each other’s knowledge can improve problem solving (Rentsch, Delise,

Table 2. Representative ITS Prompts Guiding Metacognition during the Execution Stage of the Training Cycle.

<ul style="list-style-type: none">• What do you know about the task that your teammates must know? Tell them what.• What might your teammate know that you need to know? Ask them what.• Why is certain knowledge important for your teammate to know? Tell them why.• Why is certain knowledge important for your teammate to tell you? Tell them why.• How is your knowledge connected to prior knowledge you have shared and towards some aspect of your teammate's task? Tell them connections.• How is knowledge your team member just shared connected to prior shared knowledge and/or some aspect of your task? Ask them for connections.
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Salas, & Letsky, 2010). Given this, we provide the following guideline for ITS research. Representative metacognitive prompts for the execution stage are provided in Table 2.

- *ITS Guideline 2.* ITS research can integrate metacognitive prompting that guides macrocognitive processes such as team knowledge building during the execution stage to determine how this alters collaborative problem solving.

Metacognitive Prompting during the Reflection Stage

Activities during reflection involve the review of performance (e.g., debriefing) and can involve process and performance feedback. Metacognition during this stage might involve evaluation using questions to scaffold reflection on errors occurring during the learning or performance episode (Gabelica, Van den Bossche, Fiore, Segers, & Gijssels, 2016; Hoffman & Spataru, 2008). For example, this could involve team cognitive processes associated with error detection and strategy evaluation in ways similar to team reflexivity and knowledge sharing (Gabelica, Van den Bossche, Segers, & Gijssels, 2012). In this case, team members could be prompted to reflect on what they did wrong, why they chose particular strategies, and how they could improve in future collaborative problem-solving episodes (cf. Gabelica, Van den Bossche, Segers, & Gijssels, 2014; Smith-Jentsch, Cannon-Bowers, Tannenbaum, & Salas, 2008). Quite suitable for ITSs is team reflexivity training that is adapted to macrocognitive processes. These would guide teams such that they reflect on their problem-solving objectives, strategies, and macrocognitive processes. Further, they would guide them to adapt these based upon reflection of their prior performance episodes (Gurtner, Tschann, Semmer, & Nägler, 2007). Studies in this area find that teams trained in reflexivity increase their information elaboration and this, in turn, enhances collaborative decision making during later tasks (van Ginkel, Tindale, & van Knippenberg, 2009). Given this, we provide the

Table 3. Representative ITS Prompts Guiding Metacognition during the Reflection Stage of the Training Cycle.

<ul style="list-style-type: none">• What type of errors were made during your previous performance and why?• How did you ask for information as a team and could this be improved upon?• How did you pass information as a team and could this be improved upon?• How was the team organized compared to the way you had planned?• Are there alternatives to your chosen planned and executed behaviors, and if so, what are they?• Are there any other improvements you can make to improve your performance?

following guideline for ITS research and representative metacognitive prompts for the reflection stage are provided in [Table 3](#).

- *ITS Guideline 3.* ITS research can integrate reflection-based metacognitive prompting that guides review of macrocognitive processes such as strategies, errors, and information sharing, to determine how this alters collaborative problem solving during later problem-solving episodes.

Summary

This set of metacognitive prompts provides a conceptual grounding for how to adapt team cognition theory for ITSs. It illustrates how the MITM, a theoretical guide to study complex problem solving, can be integrated with technology-based training. Granted, any such testing is best served by robust technologies capable of natural language processing. Nonetheless, embedded process and performance measures which track problem solving could also serve as guideposts for prompting. But ITSs can be flexible in their implementation of these prompts. For example, these prompts can take the form of questionnaires, spoken questions, or facilitated discussions between team members. These could also elicit telling and asking behaviors to facilitate information exchange as well as task comprehension. Depending upon the context, they can be designed to be unobtrusive (e.g., delivered in written or auditory form). Furthermore, ITSs can utilize embodied agents as teammates to deliver the metacognitive prompts.

CONCLUSION

Team cognition research continues to evolve as the need for understanding and improving complex problem solving itself grows. Complex problem solving requires members engage a number of complicated collaborative processes to generate solutions. The MITM was developed to guide research on these processes and has garnered a significant amount of empirical support. This chapter expanded upon that research to propose how ITSs could be developed to train collaborative problem solving. In particular, metacognitive prompting, based upon macrocognitive processes, was offered as an intervention to scaffold

learning these complex processes. Our objective was to provide a theoretically grounded approach for linking intelligent tutoring research and development with team cognition. In this way, team members are more likely to learn how to identify and integrate relevant knowledge, as well as plan, monitor, and reflect on their problem-solving performance as it evolves. Training in collaborative problem solving has yet to integrate metacognition and intelligent tutoring. As such, we add to this literature by providing a theoretical framework that incorporates metacognitive prompting across the stages of a training cycle. We argue that ITSs that utilize metacognitive prompting that promotes team planning during the preparation stage, team knowledge building during the execution stage, and team reflexivity and team knowledge sharing interventions during the reflection stage can improve collaborative problem solving.

This chapter outlined a specific set of representative metacognitive prompts meant to guide ITS researchers and we encourage them to pursue their study in complex problem-solving environments. Importantly, these prompts are agnostic as to the problem-solving context. As such, they are suitable for implementation as training interventions in numerous problem-solving contexts. Additionally, by framing these across the stages of the training cycle, ITS research is better able to study the relative effectiveness of prompting to determine their potential additive effects. Furthermore, by studying them separately and combined, cost-benefit analyses in learning efficacy can be completed. These, in turn, can help guide training interventions based upon the time available for trainees, and/or the competency level in collaborative problem solving. In this way, our framework is readily translatable to practical needs.

Such research is critical given the increasing complexity of socio-technological systems across domains such as aviation, aerospace, industrial process control, and the military (Letsky, Warner, Fiore, & Smith, 2008). In these environments, teams are required to solve complex problems where solutions require integration of knowledge across any number of interconnected variables distributed across people and machines (Fiore & Wiltshire, 2016; Fischer, Greiff, & Funke, 2012; Quesada, Kintsch, & Gomez, 2005). This requires that they are capable of implementing the team cognitive processes driving the collaborative efforts such that they effectively monitor and regulate their collective problem-solving performance. As the technologies being used in socio-technical systems increase in complexity, so too should the training systems. Further, our training theories must similarly increase in sophistication. In this way, we will be able to create the teams capable of solving the complex societal and scientific problems of the coming decades.

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