Antecedents of Adaptive Collaborative Learning Environments

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ABSTRACT

This paper explores the effect of critical precursors to realizing successful collaborative instructional environments in terms of their interaction within the learning effect model (Sottilare, 2012; Fletcher & Sottilare, 2013; Sottilare, 2013; Sottilare, Ragusa, Hoffman & Goldberg, 2013) and measurable relationships to team learning in the literature. We evaluated potential antecedents of successful collaborative instruction in the literature through a large-scale meta-analysis. Adaptive collaborative learning environments are group or team instruction where the challenge level of the learning experience is driven by the shared states (e.g., cognitive, affective, physical) and team performance. Independent of the computer technology, the methodology we used examined team behaviors which included, but were not limited to: cognition, communications, coordination, conflict resolution, cooperation, coaching, and leadership. Recommendations about which team behaviors are critical antecedents to the optimal selection of instructional strategies, tactics, and techniques (policies) during adaptive training and educational experiences are also discussed with respect to their effect on team learning. This research is important to the development of effective software-based agents for adaptive systems (e.g. Intelligent Tutoring Systems) where these agents are responsible for planning and executing actions based on the needs of each unique team.

ABOUT THE AUTHORS

Dr. Robert A. Sottilare leads adaptive training research within the US Army Research Laboratory where the focus of his research is automated authoring, automated instructional management, and evaluation tools and methods for intelligent tutoring systems. His work is widely published and includes articles in the Cognitive Technology Journal, the Educational Technology Journal, and the Journal for Defense Modeling & Simulation. Dr. Sottilare is a co-creator of the Generalized Intelligent Framework for Tutoring (GIFT), an open-source tutoring architecture, and he is the chief editor for the Design Recommendations for Intelligent Tutoring Systems book series. He is a visiting scientist and lecturer at the United States Military Academy and a graduate faculty scholar at the University of Central Florida. Dr. Sottilare received his doctorate in Modeling & Simulation from the University of Central Florida with a focus in intelligent systems. In 2012, he was honored as the inaugural recipient of the U.S. Army Research Development & Engineering Command's Modeling & Simulation Lifetime Achievement Award.

Dr. Joan Johnston has been a US military research psychologist for 25 years. Her current research focus is on training effectiveness with an emphasis on training transfer. Dr. Johnston's areas of expertise include training and decision support systems for tactical decision making under stress, team performance and team training technologies, embedded and distributed simulation-based training, leadership and operational readiness in joint and multinational exercises, and cross-cultural competence. She recently joined the staff of the US Army Research Laboratory, Human Research and Engineering Directorate's Simulation Training and Technology Center as a Senior Scientist. Prior to this she was the Army Research Institute Orlando Unit Chief, developing principles and guidelines for employing adaptive training technologies and mobile platform learning environments. She was a senior research psychologist for 22 years with the Naval Air Warfare Center Training Systems Division. Dr Johnston earned an M.A. and a Ph.D. in I/O Psychology from the University of South Florida.

Dr. C. Shawn Burke is an Associate Professor (Research) at the Institute for Simulation and Training of the University of Central Florida. Her expertise includes teams and their leadership, team adaptability, team training, measurement, evaluation, and team effectiveness. Dr. Burke has published over 80 journal articles and book chapters and has presented/had work accepted at over 170 peer-reviewed conferences. She is currently investigating issues surrounding: leadership within virtually, distributed teams, team cohesion, issues related to multi-cultural team performance and multi-team systems. She is also currently funded on three separate NASA grants to investigate issues pertaining to 1) multi-cultural teams, 2) team leadership, and 3) social and task roles within long duration, exploration teams, respectively. The above work is conducted with an interest in team leadership and training teams for operating in complex environments. Dr. Burke earned her doctorate in Industrial/Organizational Psychology from George Mason University and is an Associate Editor for the Journal of Trust Research and Consulting Editor for the Journal of Business and Psychology. She also serves as an ad-hoc reviewer for several journals, including: Leadership Quarterly, Journal of Applied Psychology, Military Psychology, Small Group Research. She has co-edited books on adaptability and advances in team effectiveness research.

Dr. Anne M. Sinatra is an Adaptive Training Scientist at the Simulation & Training Technology Center (STTC) within the U.S. Army Research Laboratory. The focus of her research is in cognitive and human factors psychology. She has specific interest in how information relating to the self and about those that one is familiar with can aid in memory, recall, and tutoring. Her dissertation research evaluated the impact of using degraded speech and a familiar story on attention/recall in a dichotic listening task. Her work has been published in the Journal of Interaction Studies, and in the conference proceedings of the Human Factors and Ergonomics Society. Prior to becoming an ARL Scientist, Dr. Sinatra was an ARL Post Doctoral Fellow and Graduate Research Associate with UCF's Applied Cognition and Technology (ACAT) Lab, and taught a variety of undergraduate Psychology courses. Dr. Sinatra received her Ph.D. and M.A. in Applied Experimental and Human Factors Psychology, as well as her B.S. in Psychology from the University of Central Florida.

Dr. Eduardo Salas has co-authored over 489 journal articles and book chapters and has co-edited over 25 books. He is on/has been on the editorial boards of Personnel Psychology, Theoretical Issues in Ergonomics Science, Applied Psychology: An International Journal, International Journal of Aviation Psychology, Group Dynamics, The Leadership Quarterly, Journal of Occupational and Organizational Psychology, and several others. He is past Editor of Human Factors journal and current Associated Editor for the Journal of Applied Psychology and Military Psychology. His expertise includes helping organizations on how to foster teamwork, design and implement team training strategies, facilitate training effectiveness, manage decision making under stress, develop performance measurement tools, and design learning and simulation-based environments.

Dr. Heather Holden is an assistant professor in the school of Information Technology at Mount Washington College in Manchester, NH. She previously served as a researcher in the Learning in Intelligent Tutoring Environments (LITE) Lab at the U.S. Army Research Laboratory (ARL) in Orlando, Florida. Her primary areas of research interests are technology acceptance and human computer interaction. Dr. Holden earned her Doctorate and Masters in Information Systems from the University of Maryland, Baltimore County. She also has a graduate certificate in Instructional Technology from the same university. Dr. Holden also possesses a BS in computer science from the University of Maryland, Eastern Shore.

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INTRODUCTION

The use of adaptive, computer-based technologies (e.g., Intelligent Tutoring Systems – ITSs) to support tailored learning experiences is prevalent in well-defined, individual educational domains including physics, mathematics, and software programming. Adaptive training and education (ATE) solutions are desirable additions to the blended learning solution set sought by the military community because of their significant effect on performance and learning. One-to-one human tutoring has been shown to be significantly more effective than one-to-many instructional methods (e.g., traditional classroom instruction: Bloom, 1984; VanLehn, 2011). However, one-to-one human tutoring is neither practical nor affordable in large organizations like the military (Sottilare & Proctor, 2012). A promising alternative to one-to-one human tutoring are one-to-one ATE tools which include ITSs.

Meta-analyses and reviews support the claim that ITS technologies routinely improve learning over classroom teaching, reading texts, and/or other traditional learning methods. These meta-analyses normally report effect sizes (sigma, σ), which refer to the difference between the ITS condition and a control condition, usually classroom training, in standard deviation units. The reported meta-analyses show positive effect sizes that vary from $\sigma = 0.05$ (Dynarsky et al., 2007) to $\sigma = 1.08$ (Dodds & Fletcher, 2004), but most hover between $\sigma = 0.40$ and $\sigma = 0.80$ (Ma, Adesope, & Nisbet, 2014; Fletcher, 2003; Graesser, Conley, & Olney, 2012; Steenbergen-Hu & Cooper, 2013, 2014; VanLehn, 2011). A current best estimate from all of these meta-analyses is $\sigma = 0.60$. This performance is comparable to human tutoring which varies from $\sigma = 0.20$ and $\sigma = 1.00$ (Cohen, Kulik & Kulik, 1982; Graesser, D'Mello, & Cade, 2011), depending on the expertise of the tutor. Human tutors have not varied greatly from ITSs in direct comparisons between ITSs and trained human tutors (Olney et al., 2012; VanLehn, 2011; VanLehn et al., 2007).

To capture best practices in ATE, ARL has developed the Generalized Intelligent Framework for Tutoring (GIFT; Sottilare, Brawner, Goldberg, & Holden, 2012; Sottilare, Holden, Goldberg, & Brawner, 2013), an open-source, modular architecture whose goals are to reduce the cost and skill required for authoring adaptive training and educational systems, automate instructional delivery and management, and to develop and standardize tools for the evaluation of ATE technologies. GIFT has been applied to generate adaptive tutoring concepts in military domains which include: virtual construction equipment training, military systems engineering process training, cryptography equipment training, adaptive marksmanship, game-based tutoring for medical care under fire training, and land navigation. Future applications will include: military planning, military decision-making and problem solving, and expanded applications of adaptive marksmanship.

To date, GIFT and other adaptive systems (e.g., AutoTutor, Cognitive Tutor, and Digital Tutor) have been primarily applied to individual ATE domains where interaction between an artificially-intelligent process (e.g., rules, decision trees, or software-based agents), the learner, and the training/educational environment is regulated to engage the learner and optimize learning and performance. Sottilare outlined this process known as the learning effect model (LEM; Sottilare, 2012; Fletcher & Sottilare, 2013; Sottilare, 2013; Sottilare, Ragusa, Hoffman & Goldberg, 2013; Sottilare, 2015, in press) and posits that instruction that is tailored to support the learning needs of an individual will be more efficient and engaging, and thereby more effective than non-tailored materials. The LEM is a real-time inner loop model which includes the learner, a mechanism for classifying learner states, a domain-independent planner called a strategy engine, and a domain-dependent tactical engine that selects actions and executes those actions. This model has been demonstrated extensively for task domains involving individual learners via GIFT-based tutors.

However, since the preponderance of military tasks are executed at the unit level (e.g., fire teams, squads, and platoons), the military also desires to apply ATE technologies to collaborative learning and team training task domains (Sottilare, Holden, Brawner, & Goldberg, 2011; U.S. Army Training and Doctrine Command, 2011). While GIFT has been driven by extensive prior ITS research and is designed to be adaptable for a range of individual task domains, we saw a need to adapt and grow GIFT to support adaptive collaborative learning. Adaptive collaborative learning occurs when multiple learners interact with a tutoring mechanism (Figure 1) which guides progress toward learning objectives through interaction with learners (e.g., support and direction) and interaction with the learning environment (e.g., changing the challenge level of the scenario). During these experiences, the challenge level of the scenario is driven by the shared states (e.g., cognitive, affective, physical) and team performance.

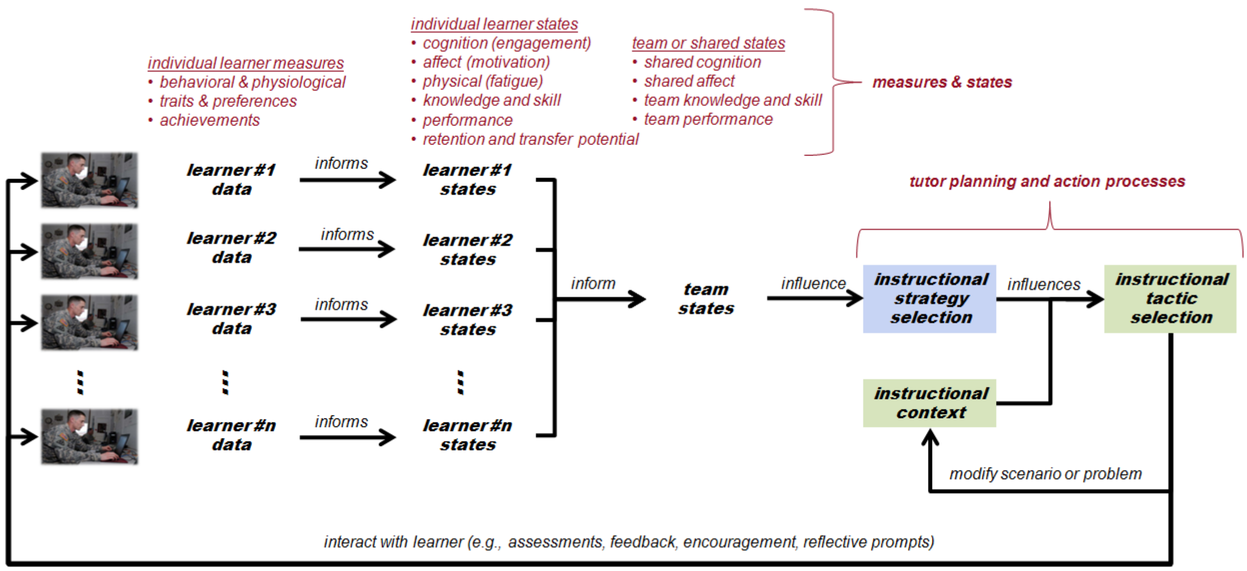

Figure 1. Updated Learning Effect Model for Team Adaptive Training and Education

The major challenge in applying ATE technologies to collaborative learning and team training is the ability to accurately model critical dimensions of team behavior, cooperation, and shared cognition with respect to their effect on outcomes like team learning. In simple terms, we define team learning to include the growth of team members in terms of their knowledge and skill acquisition. To this end, we evaluated potential antecedents of successful collaborative instruction in the literature through a large-scale meta-analysis and evaluated them in terms of a team-based LEM.

METHODOLOGY

The methodology employed to conduct our team learning meta-analysis includes a search process, search terms, a coding process, and finally an analysis process. The following search parameters were selected: (1) a finite search period 2003-2013, (2) sources include peer-reviewed journals and conference proceedings, (3) databases searched include PsycInfo, Defense Technical Information Center (DTIC), and ProQuest, (4) use of snowball approaches whereby the reference lists of identified articles such as meta-analyses, major reviews, other articles that are found in the initial search are also reviewed for additional sources, and (5) disciplines searched include psychology, healthcare, military, organizational behavior, and sports.

The following terms were used as the primary search terms for the initial review: performance, competency, trust, cognition, affect, communication, intelligent tutoring, human-computer interaction, virtual human, mood, emotion, skill, knowledge, ability, responsibilities, roles, distributed, virtual, after action review, feedback, leadership, cohesion, personality, and effectiveness. Each of these terms were paired with the following units of analysis: team, unit, group, squad, and crew and the following were used as secondary search terms: progress, goals, experience, perceptions, engagement, boredom, confusion, frustration, situation awareness, training, coordination, collaboration, motivation, cohesion, learning, leadership, training, building monitoring, goal setting, instructional strategies, debriefing, decision making, event-based training, mental models (team, shared), processes, shared cognition, simulation based training, development, transactive memory systems, backup behavior, planning, coordination, action, and transition. These were again paired with the following units of analysis: team, unit, group, squad, and crew. This resulted in identification of over 5,000 articles to be reviewed at a more detailed level. In order to increase the percentage of relevant articles, we conducted a secondary search with new search terms including, 'teams and learning', 'teams and satisfaction', 'teams and viability', 'teams and performance'. This search yielded approximately 6,000 articles. After cross-referencing the articles from these search terms with the previous ones to avoid coding duplicates there were approximately 5,991 unique articles to code.

The final dataset for the quantitative analysis process represented approximately 313 articles which met the final criteria set forth for the meta-analytic portion of the review. This resulted in over 10,000 effect sizes prior to composites being created. For the actual quantitative analysis, we followed the Hunter and Schmidt (2004) guidelines for a random-effects meta-analysis of correlations. The calculation of the composite correlations and all analyses were performed using SAS Enterprise Guide 6.1 and SAS macros that executed original syntax as well as syntax modified from Arthur, Bennett, and Huffcut (2001). Our results included a sample-weighted mean point estimate of the study correlations (r) as well as the corresponding 95% confidence interval (which expresses the amount of error in r that is due to sampling error and is used for statistical significance testing). We also include the number of independent samples (k) and cumulative sample size (N) included in the calculation of the correlation (rc) after correcting for unreliability in the predictor and criterion. Corrections for unreliability were performed using only the reliabilities reported in each article—no data was imputed. The scope of this paper is limited to team learning.

Once the quantitative coding process was complete we began to extract themes from those qualitative articles identified in the original search (e.g., the original 6,000 articles). Themes were extracted with respect to antecedents to and moderators/mediators of key relationships involving the four targeted outcomes: team viability, team satisfaction, team learning, and team performance. Here the focus was on identifying qualitative articles that were not represented in the quantitative database. This resulted in a total of 765 articles with the primary outcome foci being as follows: 516 on performance, 180 on learning, 66 on team satisfaction, and 3 on viability. The numbers presented for each outcome are actually conservative as articles often discussed multiple outcomes and the numbers reflected here represent duplicate articles having been removed from the search.

RESULTS – ANTECEDENTS OF TEAM LEARNING

While aspects of this meta-analysis may not be surprising to many, the team instructional themes and associated antecedent behaviors uncovered by this meta-analysis provide an empirical basis from which to design future strategy engines and instructional policies within ATE systems and frameworks (e.g., GIFT).

Results of the meta-analysis indicated that cooperation and its associated states contributed the most variance to team learning. Specifically, psychological safety and trust accounted for 48% and 42%, respectively, followed by cohesion with 24%. However, these individual relationships are based on only one or two effect sizes so they should be interpreted with caution. Behavioral constructs were perhaps the most studied with regard to team learning, yet overall there were just five effect sizes. Coaching and leader behaviors had the next largest impact on team learning, accounting for 30% of the variance. Empowerment behaviors were identified as influencing learning. Communication and Coordination behaviors (mainly reflexivity) all accounted for significant portions of variance in team learning (i.e., 25%, 6%, and 13% respectively). Other behaviors that accounted for significant portions of variance in team learning, but based on just one effect size were: conflict (18%), conflict management (52%), and action/transition processes (7%, 4%). The quantitative review did not uncover any aspects of context, composition, or team cognition which could be subjected to meta-analysis.

The discussion that follows examines team learning with respect to findings in six theme groups within our meta-analysis: communication, coordination, conflict, coaching, cooperation, and context and composition.

Cooperation Themes

Finding: psychological safety has a strong positive relationship to team learning. Empirical results suggest that psychological safety is a prerequisite for team learning success. Stalmeijer, Gijselaers, Wolfhagen, Harendza, and Scherpbier, (2007) investigated team learning effectiveness and performance within teacher teams, and found a positive relationship among psychological safety and all aspects of team learning behavior. In fact, the correlation between psychological safety and learning effectiveness was .86 for one of the organizations studied. Trust, an aspect of psychological safety, has also been shown to influence team learning success (Stalmeijer et al., 2007; Pierce et al., 2006). Edmondson (2003) would also argue for the role that psychological safety occupies in facilitating the ease of team members speaking up and trying out new behaviors/strategies which, in turn, increases team learning. Meta-analytic results suggest further support for this relationship, although results are only based on a single effect size (ro=.69), explaining 48% of the variance in team learning . It should be noted that the variance noted here is most likely a conservative estimate as the meta-analytic correlation could not be corrected for measurement reliability as that information was unable to be obtained for both predictor and criterion.

Finding: trust has a strong positive relationship to team learning. Another commonly investigated cooperative state that has yet to be examined in great detail with respect to team learning is trust. This relationship did not emerge as a theme during the qualitative review, yet some support is offered for its inclusion as a theme based on the meta-analytic results. Meta-analytic results indicate that it has a strong positive relationship to team learning (ro=.65), explaining 42% of the variance in team learning. It should be noted that the variance included here is most likely a conservative estimate as the meta-analytic correlation could not be corrected for measurement reliability as that information was unable to be obtained for both predictor and criterion.

Finding: cohesion has a tentative moderate positive relationship to team learning. Cohesion has a long history of being related to positive team outcomes; however, it did not appear as a commonly investigated antecedent to team learning within the qualitative review. Even within the meta-analytic database there was only one study that was found to examine the relationship between cohesion and team learning. Results, based on that study, suggest that cohesion has a moderate to strong relationship with team learning (ρ=.49), explaining 24% of the variance.

Coaching Themes

Finding: effective team leadership is positively related to team learning. Effective leadership is an antecedent to team learning. This includes continuous evaluation of learning outcomes and discussion of those outcomes with team members. An effective leader will assist the team in self-learning (Kozlowski, 1998), provide continuous feedback (Holmquist, 2007), and be motivational (Hoffman, Feltovich, Fiore, Klein, Missildine, & DiBello, 2010). Effective leaders are also adaptive in that they easily shift between these roles and alter them to serve the team's learning needs (Klein & Kozlowski, 2008). Additionally, meta-analytic results by Burke, Stagl, Klein, Goodwin, Salas, and Halpin (2006) found that person-focused leadership behaviors were strongly related to team learning and that empowerment behaviors accounted for approximately 30% of the variance in team learning.

Finding: leader coaching behaviors must be done at the correct temporal point in the team's life span to have maximal learning effectiveness. Hackman and Wageman (2005) define team coaching as, "direct interaction with a team intended to help members make coordinated and task-appropriate use of their collective resources in accomplishing the team's work" (p. 269). Hackman and colleagues argue that there are three broad classes of coaching behaviors (i.e., motivational, strategy-focused, and educational) and that their instrumentality varies dependent on temporal factors. While all three are important, perhaps most relevant to facilitating team learning are the latter two. Strategy-focused coaching behaviors are those which focus on the development of members' knowledge and skill. It has been argued that the end of the performance period is when teams will engage in reflection and this is when they will also have the greatest amount of data from which to explore learning opportunities based on individual and collective reflection and feedback which are indicative of educational coaching behaviors (Hackman & Wageman, 2005). These types of leader behaviors serve to cause team members to metacognitively reflect on the past performance actions in a systematic manner such that team learning can occur. Team self-correction is one such educational strategy that has been shown to increase learning in teams (e.g., Smith-Jentsch et al., 1998). In contrast, educational coaching behaviors are those which tend to be more strategic in nature and are often the most helpful at the team's midpoint where research has shown (Gersick, 1988) that teams have a natural tendency to reflect on how strategy is working compared to the team's endpoint.

Communication Themes

Finding: communication has a strong positive relationship with team learning. When a team is involved in efforts to learn, not only are team members interacting with the learning content, but they also have the opportunity to learn from each other. This places importance on the team's ability for social interaction with one another. Through communication and interaction with fellow team members, team members are able to learn from one another leading to increases in cognitive skill development, knowledge, and understanding (Ardaiz-Villanueva, Nicuesa-Chacon, Brene-Artazcoz, de Acedo-Lizarraga, & de Acedo-Baquedano, 2011).

Effective communication is an antecedent to team learning. This includes communication between team members, as well as communication between team leaders and members. Effective communication between team leaders and members involves leaders giving feedback during the learning process (Hawley & Mares, 2007). Discussion and reflection of feedback between team members can further enhance learning (Helstad & Lund, 2012; Holmquist, 2007). Meta-analytic results support the findings put forth in the qualitative literature in that communication was found to explain a significant 25% of the variance in team learning (ρ=.50).

Finding: collaborative learning facilitates positive learning outcomes. Collaborative learning leads to higher learning outcomes. Collaborative learning is achieved by sharing expertise, sharing knowledge, and actively participating in the team. Collaborative learning may be increased by motivational instruction (Hoffman, Feltovich, Fiore, Klein, Missildine, & DiBello, 2010). Two things that may interrupt collaborative learning are performance pressure and nonparticipation. The process of sharing expertise may be impeded by increased performance pressure (Gardner, 2012), which may then affect the learning process. Nonparticipation directly interferes with the learning process (Karpova, Jacobs, Lee & Andrew, 2011).

Coordination Themes

Finding: coordination has a small to moderate positive relationship with team learning. Although team coordination did not emerge as a theme based on the qualitative review for the time period covered, it does emerge based on the quantitative review. Meta-analytic results indicate that coordination accounts for a significant 6% of the variance in team learning (ρ=.25).

Finding: reflexivity has a moderate positive relationship with team learning. Reflexivity or "the extent to which team members collectively reflect on and adapt their team's objectives, strategies, and processes" (Tjosvold, Tang, & West, 2004, p. 542) did not emerge as a theme based on the qualitative review, but does when examining the quantitative review. Meta-analytic findings, based on two effect sizes, indicate that reflexivity explains a significant 13% of the variance in team learning (ρ=.36). While not reflected in the qualitative review the relationship between reflexivity and team learning makes conceptual sense and is in line with the work on team self-correction (Smith-Jentsch, Cannon-Bowers, Tannenbaum, & Salas, 2008).

Conflict Themes

Finding: conflict has a tentative moderate negative relationship with team learning. In looking at the qualitative literature during the time period covered by this review, team conflict did not emerge as a theme with regard to team learning. However, in examining the quantitative literature, one study examined this relationship and met the criteria to be included in the meta-analytic review. Results suggest that conflict has a moderate negative relationship with team learning (ρ=-.43) explaining 18% of the variance. However, given that this did not emerge as a theme based on the qualitative literature and the finding is represented by only one study in the meta-analytic database, we posit this theme as tentative. This result should be interpreted with caution.

On a related note, conflict management was found to explain a significant 52% of the variance in team learning (ρ=.72). While meta-analytic results suggest a strong positive relationship between conflict management and team learning, this finding was based on only one effect size. Therefore, it should be interpreted with caution and is not being given its own theme. However, it does make theoretical sense from the standpoint that the management of conflict should facilitate the information sharing and interactions which facilitate team learning.

Context and Composition Themes

The extraction of themes with regard to the role of context and composition in relation to team learning has been conducted primarily based on qualitative review. The predominant amount of quantitative studies that were identified for inclusion in the meta-analytic database do not have the number of effect sizes that would be needed to conduct moderator analysis that would empirically investigate the role of context. The following findings related to context and composition themes were discovered:

- *The climate of the team will facilitate learning*
- *Organizational climate influences learning effectiveness*
- *The degree of virtuality can impact the team's learning process*
- *Simulation fidelity and immersion can play an important role in team learning efforts*
- *Compositional factors may influence team learning processes through means of psychological safety*
- *Composition of learning styles of the team members can facilitate collaborative learning*
- *Cultural diversity may facilitate team learning (if information sharing barriers are overcome)*
- *Role diversity in a collaborative task can provide multiple perspectives, facilitating learning for team members*

Relationships between Team Learning Antecedents

An examination of the meta-analytic correlations indicate that the covariance among the key constructs which are significantly related to team learning varies greatly dependent on the particular construct of interest.

Some of the strongest positive relationships are seen with respect to: (1) psychological safety and collective efficacy (ρ=.76), (2) cohesion and trust (ρ=.70), (3) communication with conflict management (ρ=.68) and trust (ρ=.68). A strong negative relationship is seen between psychological safety and conflict management (ρ=-.82). While weak relationships (non-significant relationships) are seen with respect to: communication and conflict (ρ=-.09), trust and coordination (ρ=.03).

DEVELOPING ATE GUIDELINES

Understanding the influence of team behaviors in the themes discussed above is one step in a larger process. If we understand how these themes influence team learning, we can use them to improve the effectiveness of team instruction by providing timely, targeted, and effective interactions with learners and the ATE environments. The next step in our research is to develop ATE policies and guidelines based on the findings noted above and conduct experiments to validate the accuracy and consistency of the decisions made by ATE systems. To do this we must be able to measure the behaviors in the themes noted and then be able to select appropriate actions that will optimize learning either by initiating or maintaining desirable behaviors, or ending undesirable behaviors.

For example, our findings that *effective communication has a strong positive relationship with team learning* may be used to generate multi-agent policies that track communications between team members. Understanding that communication is happening on a regular basis between team members with interdependent roles may be enough. However, it may be necessary for ATE systems to assess the level of effectiveness of each expected communication in terms of its potential influence on positive states or mitigation of negative states with respect to team learning.

Behavioral and physiological measures as well as progress toward learning objectives may be captured and analyzed to inform individual learner states. Assessment of team states through behaviors, roles and tasks are more complex (Bonner, Gilbert, Dorneich, Burke, Walton, Ray, and Winer, 2015). In the case of our team communication model, we are interested in communication performance. The individual communication performance states are domain-specific and composed of attributes which include: a communication partner, when the communication occurred, what was said, where it was said, and perhaps why it was said (e.g., motivation for communication). The communication performance of all the team members along with the other learner states and traits is used to develop a shared communication state for the team. Based on the team communication state, the ATE system selects an optimal strategy (plan for action). In our example, the ATE system may decide to implement a tactic to provide feedback to the team, provide feedback to selected members, or modify the scenario or problem to increase/decrease the challenge level. How selections are made can vary from rules to decision trees to Markov decision processes (MDPs), but the central focus is for the ATE system to make decisions which optimize deep learning within the team. According to Puterman (2014), MDPs, also known as stochastic dynamic programs or stochastic control problems, are models for making decisions when outcomes are uncertain. This certainly fits well with our ATE system definition since our evaluation of learner states is less than 100% accurate. MDP models include current and future states, actions available, rewards associated with actions, and transition probabilities. Policies or strategies govern which optimal action to choose under every decision encountered.

The adaptive instructional process can be generalized for each learner in a team as shown in the MDP pictured in Figure 2. Each learner is determined to have an initial state from which a finite number of actions (A_1, A_2, and A_3) are available to the learner. Taking a specific action will result in a probability of moving from their current state to a new state or remaining in their current state. The new state may be optimal for long term team learning (green learner states) or it may not be (pink learner states).

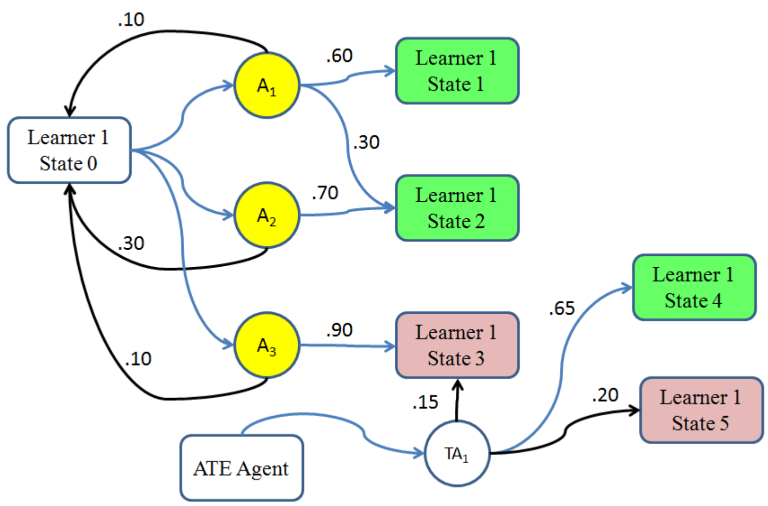

Figure 2. Markov Decision Process for Individual Team Members

For example, at State 0, learner 1 selects action 3, and moves to State 3, a suboptimal state for team learning. In State 3, it may not be possible for Learner 1 to self-regulate and move out of this suboptimal state without help. In this case, the ATE agent recognizes this learner is in a suboptimal state and takes action (TA_1) which results in three possible outcomes: movement to State 4 (optimal), movement to State 5 (new suboptimal state) or remaining in State 3 (suboptimal) until such time that either the learner or the ATE agent initiates an action that moves them to a new state. Blue arrows indicate progress while black arrows indicate stagnation or regression. The numbers in the decision process indicate the probability of the learner moving from one state to another based on a given action.

RECOMMENDATIONS AND FUTURE RESEARCH

Most traditional ATE systems are time consuming and costly to develop. By adding the requirement of developing team-based ATE, a difficult problem has become even more complex. In order to tackle the problem it is important to start with a strong foundation in the literature. The findings of this meta-analysis can be used as an initial basis to structure and develop team-based adaptive instructional strategies and policies. The integration of findings from our quantitative review and its application to ATE agents is a promising avenue for future research. Currently, these models are still under development and we urge others to work on fine-tuning, validating, and increasing the complexity of behavioral and physiological measures.

First, we call for attention to the idiosyncrasies that may occur when ATE systems are targeting a team rather than just an individual. Models for an expanding variety of individual training domains (e.g., military planning, military decision-making and problem solving, and adaptive marksmanship) are beginning to emerge through GIFT. However, applying individual-focused findings and expanding to a higher level of analysis for team brings a number of challenges. For instance, it is important to test whether the individual-level links are homologous to the team-level (e.g., increasing individual's knowledge will also increase team's knowledge?). Second, a number of boundary conditions is likely to emerge that may hinder or enhance the shared states and team learning. Even though we identify communication, collaborative learning, coordination, reflexivity, conflict, conflict management, coaching, psychological safety, trust, and cohesion as facilitators of team learning, contextual and compositional variables still play a role that should be further explored (e.g., virtuality, climate, composition of learning styles, etc.). Consequently, a more thorough investigation of moderators for each link can provide us with a better understanding of systematic differences. Third, we urge researchers to invest on in examining a broader picture on how teams work. During ATE experiences, ITSs will have to deal not only with the progression of a learner, but also with the shared learning and the pattern in which the learning trajectory takes with each team. The research discussed in this paper has started to shed some light on the potential to facilitate team learning, but future research should address the gap of understanding how these constructs work simultaneously. The development of effective software-based agents for adaptive systems requires a great level of specificity and complexity. In this vein, initial steps are being taken within the GIFT framework to support team-based tutoring and research (Walton, et al., 2014).

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