Multimodal Measures for the Integration of Metacognitive Teamwork Processes During Simulation-Based Training

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INTRODUCTION

Teamwork is a critical and direct component driving the success of teams within extreme environments (e.g., military teams in war zones; Meslec et al., 2020). Teamwork includes a collection of cognitive, affective, verbal, and behavioral interactions between individual team members directed towards achieving a common goal (Kozlowski, 2018). The importance of teamwork for team performance has elicited the development of training methods and devices that aid in individual team members' ability to provide the skills necessary to effectively contribute to team performance (Vatral et al., 2022). For military training, this includes game-based learning environments (Martín-Hernández et al., 2021), wargames (Dorn et al., 2020), and live training (Johnston et al., 2022). In order for these training approaches to be effective, it is imperative that teamwork and team performance have valid and reliable measurements that can also be used to provide constructive feedback (Nonose et al., 2014). Typically, these measures are reliant predominately on behavioral markers that trained experts evaluate through observation. However, recently there has been a shift to introducing virtual simulations as effective training methods of teamwork for military scenarios (Balint et al., 2020; Johnston et al., 2019) as simulations offer several affordances that enhance how researchers are able to effectively observe, capture, track, and evaluate teamwork (real time and over time) for enhanced team performance outcomes (Goldberg et al., 2021). These new affordances may also provide a path by which less directly observable processes (i.e., metacognition underlying situational awareness) can be collected and integrated into teamwork metrics.

This paper proposes an extension of the hierarchical Affective, Behavioral, Cognitive (H-ABC) framework (Vatral et al. 2022) to incorporate metacognitive processes to further our assessment of teamwork within simulation-based training utilizing the Multimodal Observational OpenVR (MOOVR) Toolkit. We ground this expansion within a brief overview of our in-development, virtually simulated army battle drill (2A – Conducting a Squad Assault). Using this framework, we detail our approach to automatically assess individual-level and team-level performance using multimodal data that can then be integrated with GIFT (Generalized Intelligent Framework for Tutoring; Sottilare et al., 2012; Sottilare et al., 2017). Finally, this paper proposes several recommendations for potential metacognitive skills and competencies that can be operationalized with multimodal learning analytics derived from video, audio, gestures, head positioning, physiological responses (i.e., electrodermal activity and heart rate), log-files, and self-reports collected in (near) real-time during a simulation-based training exercise (Azevedo et al., 2018; Wiedbusch et al., 2023).

METACOGNITION DURING TEAMWORK

Adaptation of one's cognition and behavior lie within metacognition, often colloquially defined as one's thinking about their thinking (Flavell, 1976; Winne & Azevedo, 2022). However, more specifically, metacognition refers to one's ability to (in)accurately reflect on, evaluate and control first-order cognitive processes (e.g., decision-making, perception, and memory; Katyal & Fleming, 2024). While a large body of research and theory on metacognition exists (Tarricone, 2011; Fleming, 2024; Norman et al., 2019), there is still much debate over what does (and does not) constitute metacognition or a unifying framework that distinguishes between cognition clearly (Azevedo, 2020). However, across the many theoretical models of metacognition (e.g., Nelson & Narens, 1990; Winne, 2018) there are several metacognitive processes that can be roughly categorized as either monitoring/evaluative processes or as regulatory processes. Monitoring processes may include making evaluative judgements (e.g., feelings-of-knowing, judgements of learning, etc.) and reflection (Greene & Azevedo, 2009). Metacognitive regulatory processes may include selecting appropriate strategies, planning, and making changes to current learning/training approaches.

When performing as an individual, this monitoring and regulation allows us to adapt to volatile environmental factors (e.g., such as seen on a battlefield). The more accurate one is at making metacognitive judgements and evaluations, the more appropriately they can regulate their behavior, cognition, and affective processes which ultimately results in better performance outcomes (Fleming, 2024). When performing in a group, however, social metacognition, also referred to as team or group metacognition, expands these typical processes to include information processing and regulation about team performance, affect, and group dynamics (Folomeeva & Klimochkina, 2021; Thompson & Cohen, 2012). That is, in addition to monitoring and controlling our own knowledge, emotions, and actions, during social metacognitive processing, we are now additionally tasked with monitoring and regulating our team's knowledge, emotions, and actions. While many models of teamwork exist (e.g., Cooke et al., 2007; Endsley & Jones, 2001), many of these models represent cognition in teams as the sum of individual cognition while neglecting the cognitive factors that may influence cooperation (Nonose et al., 2014). As such, we see the opportunity to enrich these approaches with the affordances that virtual-reality (VR) simulations may provide to helping capture, measure, and provide feedback for less observable teamwork behaviors.

CASE-STUDY: BATTLEDRILL 2A – CONDUCTING A SQUAD ASSAULT

Figure 1. Example of the Battle Drill 2A drill being conducted in the UCF Arboretum (left) used to inform the design and development of the virtual-reality simulation environment (right).

To contextualize the extension of this framework and the ongoing VR simulation development, we will use a case study of Battle Drill 2A as the task. In this drill, one squad leader and two infantry fire teams of four members each are moving as part of a platoon towards contact or an attack when the enemy initiates direct fire. The squad's goal is to locate, suppress and neutralize the enemy. In our VR simulation, the two fire teams are – Team Alpha and Team Bravo. Team Bravo will be comprised of human users working together with an artificial intelligence (AI)-driven squad leader and Team Alpha, an infantry team consisting of AI-driven agents/squad members. The drill should take approximately 5 to 10 minutes to complete, and we anticipate each team will perform 3 to5 iterations of the drill.

Data will be collected on events, movements, body gestures, head movements, log files of human-computer interactions (HCI), verbalizations, electrodermal activity, and heart rate data from the human users using a combination of GIFT and the Capturing and Logging OpenVR (CLOVR) open-source tool (Segarra Martinez et al., 2024). CLOVR is a tool for collecting data from any VR application built with the OpenVR API (Application Programming Interface), including closed-source VR consumer games and experiences. It supports capturing and logging VR device poses, VR actions, microphone audio, VR views, VR videos, and even the presentation of in-VR questionnaires. We are currently creating a new version of CLOVR that is compatible with other VR software development kits (SDKs) aside from the OpenVR SDK, such as the Meta SDK, which we call the Multimodal Observational OpenVR (MOOVR) Toolkit. This will allow us to also capture eye tracking data by using the Meta Quest Pro headset in conjunction with the MOOVR Toolkit. All of the data captured with MOOVR will be made available to the GIFT framework to afford long-term data tracking on an individual user basis. Below, we discuss more in detail about the multimodal metrics that will be further incorporated within our GIFT implementation as a multidimensional measure of teamwork metrics at both the individual and the team levels.

THEORETICAL FRAMEWORK

Simulation based training has benefited from the ability to automatically evaluate learner performance using multimodal data instead of relying on manual analysis by domain expert review (Azevedo & Wiedbusch, 2023; Biswas et al., 2020; Goldberg et al., 2021; Vatral et al., 2022). This is typically accomplished by capturing traces of user behaviors during the simulation to make inferences about learning and cognitive, behavioral, affective, and metacognitive processes based on theory (Winne & Azevedo 2022). In addition to traditional audio and video data of the learner going through the simulation-based training environment, other objective measures can be captured using eye-tracking, gesture-recognition, and physiological data (e.g., heart rate, electrodermal activity), in addition to subjective measures collected via self-reports and verbalizations. However, all these data must be contextualized within both the task and a theoretical model of the performance metrics.

Our work is an extension of the hierarchical Affective, Behavioral, and Cognitive model of teamwork (H-ABC; Vatral et al., 2022). According to this model, teamwork is comprised of a series of temporally dynamic affective (e.g., mutual trust, self-efficacy), behavioral (e.g., communication, coordination), and cognitive (e.g., team mental models, team learning) processes. These processes can be organized into a multi-level hierarchical structure in which more high-level abstract teamwork processes can be directly linked to low-level directly observable skills and competencies specific to a context or domain. This model continues to be updated and improved upon through iterative empirical work to allow for more explicit mapping of measures to context-specific skills, knowledge, and abilities. However, this model does not explicitly include metacognitive processes currently. As previously described, metacognition, or the monitoring and regulation of first-order cognition, is essential for individuals to make evaluations and reflections of their performance to modify and adapt to changing conditions and standards (Katyal & Fleming, 2024). Group metacognition can strengthen the accuracy of this monitoring through discussion of experiences, perceptions, and evaluations especially in the absence of objective feedback (Wolfe, 2018).

Below, we describe our extension to the H-ABC framework to include metacognition at the highest abstraction level (among affect, behavior, and cognition), several mid-level processes (i.e., planning, evaluation, and reflection), and several context-specific low-level skills and competencies (e.g., setting goals, identifying gaps in task understanding). This expansion pulls from multiple theories of metacognition (e.g., Greene & Azevedo, 2009; Lobczowski, 2022) and socially shared regulation of learning (e.g., Järvelä et al., 2023).

Extending H-ABC to Integrate Metacognitive Team Collaboration Processes

Our extension focuses on the addition of metacognitive processes; however, we also slightly adapt levels 4 and 5 to our current study to highlight the distinction between individual and team metrics and the specific multimodal data measures of those metrics respectively. According to this extension, we consider metacognition as a level 1 process akin to affect, behavior, and cognition. While by definition, metacognition includes the regulation of first order cognition, we have refrained from making any interactions across level 1 processes explicit. Instead, we consider these interactions through their joint influence on subprocesses. For example, we define "Team Cohesion", a level 2 sub-process, as a metacognitive-affective process. We show that metacognition theoretically exhaustively influences each of the defined level 2 sub-processes (see Table 1) based on various literature in the field.

Table 1. Literature exemplars theoretically justifying each Metacognitive -> Level 2 sub-processes connection

Level 2 Sub-Process	Description	Exemplar Literature
Team Cohesion	The shared multidimensional desire/bond that drives teams to want to work and stay together that includes common/shared tasks and goals, social relationships, sense of belongingness, group pride, and morale (Salas et al., 2015)	Garrison, 2022 Kozlowski & Chao, 2012; Lobczowski et al., 2021;
Psychological Safety	The evaluation of how "safe" individuals within a team feel in bringing up certain subjects or seeking assistance (Edmondson, 1999)	Dibble et al., 2019; Thompson & Cohen, 2012 Tucker et al., 2006
Cooperation	A structure for joint interaction towards a defined task or goal (Panitz, 1996)	Cheong, 2010; Nonose et al., 2014; Stevens et al., 2016
Communication	The explicit expression of ideas through words, actions, and facial expressions (Dillenbourg & Traum, 2006)	Carlson, 2016; Folomeeva & Klimochkina, 2021; Joksimovic et al., 2020
Coordination	The dynamics of team member interaction and the environmental dynamics they are acting within under a shared mental model (Gorman et al., 2010)	Thompson & Cohen, 2012; Keestra, 2017; Kwon et al., 2013;
Shared Mental Models	The team's internal representation and cognitive structure of their task, team, interactions, and environment (Jonker et al., 2010)	Gorman et al., 2010; Thomspon & Cohen, 2012; Mohammed et al., 2017
Shared Perception	The symmetrical awareness of each individual's understanding of their environment including any unique affordances or limitations due to incomplete information or abilities (Matarese et al., 2022)	Gormon et al., 2010; Jamil et al., 2023; Järvelä & Hadwin, 2013

Additionally, we have included three new level 2 sub-processes – (1) reflection, (2) evaluation, and (3) planning (Greene & Azevedo, 2009; Lobczowski, 2022). Reflection refers to the monitoring of one's cognition about their practice (i.e., behavior or approach) to make adjustments (McAlpine et al., 1998). Reflection, in our context, therefore, is directly related to the monitoring of team performance. Evaluation refers to the monitoring and appraisal of one's affect, behavior, and cognition relative to plans and goals (Greene & Azevedo, 2009; Lobczowski, 2022) which may then trigger future changes in response. We have theoretically tied evaluation to the mutual performance monitoring, adaptability, and task comprehension level 3 sub-processes. Evaluation is vital for adaption to changing environmental factors and team dynamics. For example, if we are unable to recognize a changing affective atmosphere in response to an environmental change (e.g., failing to recognize growing group frustration or heightened arousal during an ambush), we may then fail to act accordingly (e.g., emotionally regulate to avoid impulsive behavior) resulting in lowered team performance. Finally, planning refers to the coordination of selecting cognitive processes that once executed behaviorally will result in a change in state towards a set of (sub)goals (Greene & Azevedo, 2009). While traditionally we think of planning as happening only prior to any task performance, planning can happen intermediately throughout a task as an individual evaluates and reflects on their current state before choosing next steps. As such, we have directly tied the level 3 subprocesses of adaptability and task-comprehension to planning.

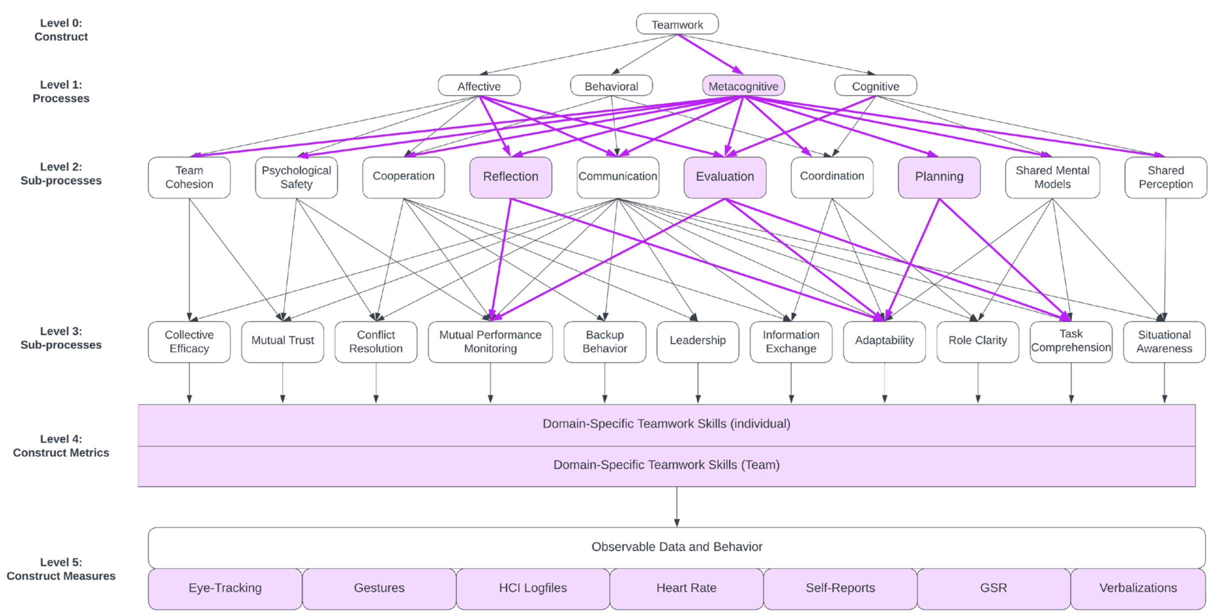

Figure 2. The revised H-ABC model for evaluation of teamwork behaviors, as developed in Vatral, et al. (2022) to include metacognitive processes (additions highlighted in purple).

In addition to the new metacognitive sub-processes on levels 2 and 3, our extension highlights a distinction within the level 4 construct metrics of teamwork. Specifically, we identify that under our context we will have metrics for both the individual and the team. Teamwork by a team involves more than just a collection or aggregation of simultaneous coordinated individual actions, but rather may be considered an emergence of coordination and joint actions (Cohen & Levesque, 1991; Gorman et al., 2017). That is, it is a dynamical system (Gorman et al., 2017) that requires advanced modeling approaches using a multimodal data approach to measuring the various metrics at both the individual and team (i.e., system) level. We have identified the data sources we will be using in our context within level 5 and provide a brief explanation of these measures below.

Multimodal Measures of Metacognition in Team Collaboration

As we have previously established, VR simulations are positioned to provide rich traces of affective, behavioral, cognitive, and metacognitive processes that are traditionally inferred in observation-only based assessment of team performance and teamwork. Multimodal trace data is highly valuable in its ability to provide unobtrusive insights into various psychological constructs and processes as they unfold in real time (Azevedo & Gasevic, 2019). Furthermore, having multiple streams (or sources) of data can allow us to combine and fuse across modalities to provide more context-rich data and interpretations than a singular channel can provide alone (Wiedbusch et al., 2023). This holds especially true for the black box that is cognition and metacognition in which these processes must be inferred from observable behaviors (Azevedo & Wiedbusch, 2023).

Adapted from the learning analytics field (Ochoa, 2022), we will follow a similar construct mapping process in which each of our level 4 psychological constructs (e.g., “squad member identifies gap in task understanding”) are mapped to observable behaviors (e.g., verbalizations between team members, gross level movement away from objectives, head tilts or prolonged examination of objective instructions). These behaviors collected via a suite of available multimodal data captured and synchronized using the MOOVR Toolkit including environmental or user events, movements, body gestures, head movements, log files of HCI, verbalizations, electrodermal activity, and heart rate data. Within each of these behaviors are multiple analytics or metrics that can be compiled. For example, it could be the frequency of task questioning utterances (e.g., “I don’t know what I am supposed to do here? What are we doing? What needs to be done?”) or the dwell time on instructions or team leader providing instructions (and the associated deviation from the average expected dwell time). It is important to note that there can be multiple behaviors associated with each teamwork construct and multiple analytics that can be derived from each observable behavior. After our first study, our team will be examining the optimal number of these behaviors and analytics that are required to best capture and model each construct to help reduce the number of dimensions and analytical resources required from this approach.

IMPLEMENTATION IN GIFT

Next, we briefly outline our proposed implementation of our integrated feedback framework in GIFT. The work described in this paper is planned to be integrated into GIFT after it has been developed. There are two approaches in which it can be applied in GIFT: technical and theoretical. From a technical perspective, GIFT has previously been integrated with Unity, which will allow for information to be passed between the Battledrill 2A scenario that is in development and the gateway module in GIFT. The assessment of performance during the scenario can be implemented through the scenario itself as well as in a domain knowledge file (DKF) in GIFT. It is anticipated that some of the generalizable assessments, and relevant condition classes which assess behaviors could become part of the standard condition classes included with GIFT. From a theoretical perspective, the development of GIFT has continually been rooted in theory. The initial H-ABC model (Vatral et al., 2022) continues to provide a theoretical basis that can be applied in GIFT, and the addition of metacognition adds a new dimension that can also be tracked and utilized for adaptivity in GIFT.

CONCLUSIONS AND FUTURE DIRECTIONS

Effective implementation of automatic feedback in an intelligent tutoring system demands a strong theoretical grounding to make constructive interpretations of multimodal data signals for inherently noisy and complex tasks that involve large teams. In this paper, we describe a theoretical expansion of a model of teamwork to include metacognition (at the individual and group level) while exploring what type of data may be best for the collection of these processes' traces during simulation-based training. Metacognitive processes of planning, evaluating, and reflecting are what drive team adaptability to complex and rapidly shifting environments. Their inclusion within models of teamwork is inherently messy due to the entanglement of metacognition, cognition, affect, and behavior. However, we argue that the inclusion and acknowledgement of these processes for application far outweigh the loss of some distinction between process origination at higher levels within the model.

In addition, we discussed the future implementation of our multimodal measures of teamwork metrics within GIFT to be used as an assessment and feedback tool for simulation-based training. By offering data outside of traditional subjective expert graded performance feedback, we anticipate learners will be able to garner a more holistic view of not only their individual but team level performance to target specific skills, behaviors, and strategies in future iterations of training. Future work on this project will include the development of an analytical after action review to be integrated with GIFT to provide actionable feedback and performance review.

While this work above is in the initial theoretical development of expanding a framework, we are also designing a series of empirical studies by which to refine this framework and inform future work. These studies will be conducted to train our models of team dynamics and performance and assess the impact of various multimodal signals as indicators of teamwork during simulation-based training. Based on the outcome of these future models, we will continue the development of a VR environment with adaptive and intelligent artificial agents capable of performing as a team with human counterparts to help reduce cost and supplement current approaches to team training.

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