Chapter 3 – Graphical Supports for Collaboration: Constructing Shared Mental Models

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INTRODUCTION

Graphical images are useful in helping teams develop shared mental models, particularly when digital tools enable team members to co-construct these representations. For example, the use of concept maps as external representations of knowledge, in a form that can be manipulated and reasoned with, can clarify thinking, focus a task, facilitate collaboration, and reduce cognitive load. This chapter describes several types of graphical supports—concept maps, 3-dimensional cognitive mapping, and self-visualizations—as ways to enable the collaborative construction of shared mental models.

Concept Mapping as a Representational Structure that Enables Shared Mental Models

Concept mapping as a representational structure is an effective mechanism for students to express their conceptual understanding (Novak, 1990; Rice, Ryan, & Samson, 1998; Rosen & Tager, 2014; Toth, Suthers, & Lesgold, 2002). The use of concept maps as external representations of knowledge, in a form that can be manipulated and reasoned with, can clarify thinking, focus a task, facilitate collaboration, and reduce cognitive load (Cox, 1999; Jonassen, 2003). In particular, computer learning environments for inquiry-based science learning have the opportunity to include electronic concept mapping as a knowledge construction tool. Students engaging with computer based simulations and virtual worlds may develop a deeper understanding about the dynamic systems represented in these environments through engaging in concept mapping of the system as a map of causal relationships between its factors. Michael Zeilik's website (http://archive.wceruw.org/cl1/flag/cat/conmap/conmap1.htm)

EcoXPT is a multi-user virtual environment (MUVE)-based middle school science curriculum that supports learning about the causal dynamics of ecosystems through observation, exploration, and experimentation in a virtual world (Dede, 2017; Grotzer, 2017). It builds and expands upon earlier research with EcoMUVE (Metcalf et al., 2011, Grotzer et al., 2013). EcoXPT supports situated learning – students conduct scientific inquiry while immersed in the richly represented ecological setting, interacting with virtual people and organisms, collecting and analyzing data. As a culminating activity, student teams engage in construction of a concept map as a representation of the components, processes and relationships relevant to the phenomena identified in the ecological scenario.

In prior research with EcoMUVE, students were instructed to draw concept maps on paper. For EcoXPT, it was hypothesized that students might be better supported with an integrated computer-based concept map tool. In particular, it was considered that providing a structured tool for concept mapping might scaffold students in concept map construction to support deeper learning about the causal relationships in the system. Additionally, by integrating the tool with the virtual environment, it might support students making more connections between data collection, data analysis, and hypothesis constructing activities.

The EcoXPT curriculum consists of a two week, inquiry-based unit centered on a virtual pond and the surrounding watershed. Students explore the pond, learn about the plants and animals in the ecosystem, and travel in time to see changes over the course of a virtual summer. They discover on one day that all of the large fish have died, and are given the inquiry task of figuring out why it happened. The system models an eutrophication scenario in which fertilizer runoff induces excessive algae growth. Then the algae die off and, as bacteria decompose the dead matter, the bacterial population surges. This combination of factors--coupled with weather conditions of warm temperatures, cloudy days, and low wind--lead one evening to dramatically lowered dissolved oxygen in the pond that causes the death of all of the bluegill and large-mouth bass in the pond, although the minnows, which can survive in relatively low dissolved oxygen conditions, do survive.

EcoXPT includes a range of integrated tools that support students in learning about the pond and its surroundings. Students can make observations, photograph organisms in and around the pond, shrink to view microscopic organisms, and travel in time. They collect measurements about the water (e.g., phosphates, temperature, dissolved oxygen), weather (e.g., wind speed, cloud cover), and populations of organisms (including three species of fish, two types of algae, and bacteria); then the view graphs showing trends in the data over time. They use reference tools such as an online field guide and an atom tracker, and gather testimony from characters in the world. The pilot version of the curriculum used in this study also included a lesson on drawing concept maps to represent the causal relationships in an ecosystem.

Students collaborate in teams to solve the mystery, working together to collect and analyze data in the virtual world. As a culminating activity, each team of students constructs and presents to the class a poster that represents their hypotheses to explain why the large fish in the pond died. The team posters are required to include a concept map, a written summary of their hypothesis, and printouts of the evidence they used to support their ideas.

This study piloted a new electronic concept mapping tool that was designed to scaffold students' concept mapping activities. The tool (Figure 1) provided a pre-defined palette of factors designed to represent all of the variables that student were able to observe or measure in the virtual world. Students drag factors out of the palette to place them as nodes in the concept map, and drag a link from one node to another to create connecting arrows representing causal relationships between factors.

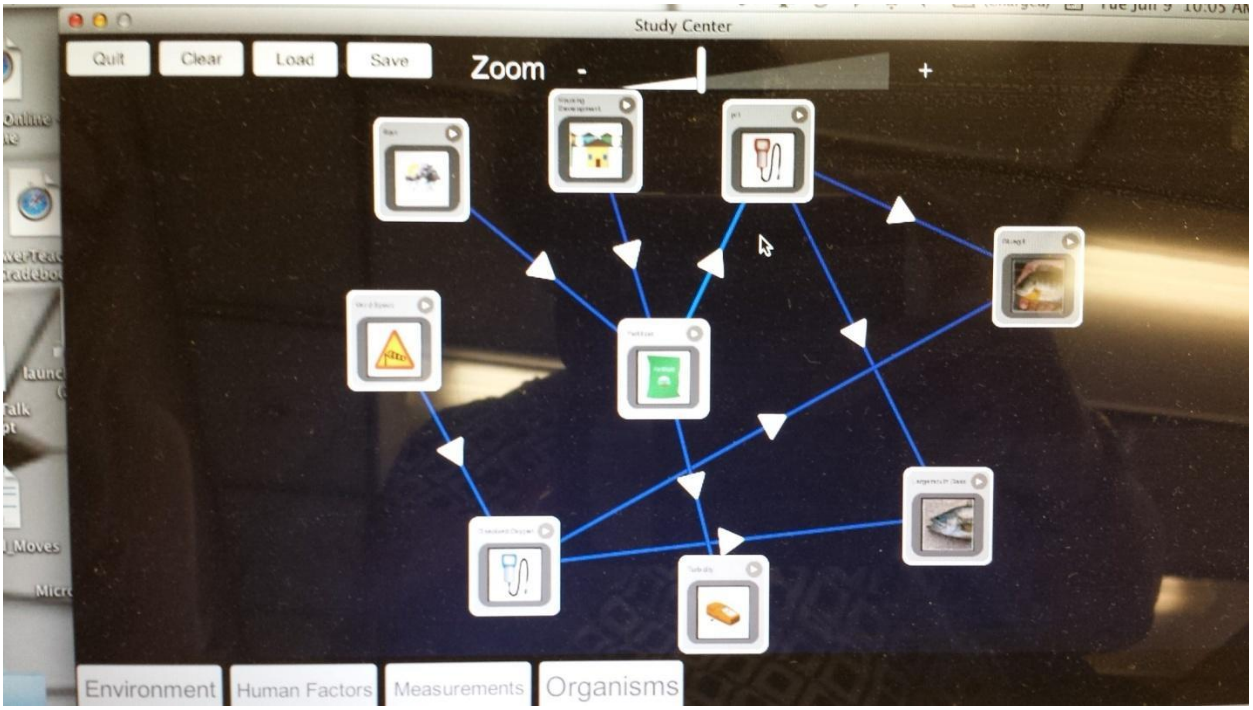

Figure 1: Photo of concept map being constructed on screen

In a pilot study, students who used the electronic concept map tool constructed larger and more complex concept maps than similar teams doing concept mapping on paper. This finding appears to support the proposal that providing external structure for concept mapping can scaffold collaborative activity by teams of students. In particular, the increase in number nodes in the electronic concept maps is likely caused by the fact that the software tool provided students with a large set of pre-defined nodes to use, potentially fostering convergence.

3-Dimensional Cognitive Mapping as a Representational Structure that Enables Shared Mental Models

In inquiry-based learning contexts, many students experience difficulties managing the complex inquiry process and engaging in fruitful inquiry learning. The inquiry process often involves iterative cycles of gathering information through observation or experiments, generating hypotheses, reasoning based on the collected information, and drawing conclusions. Many students find it cognitively demanding to integrate problem data with subject knowledge and to reason with intricately intertwined data. It is therefore necessary to guide students through the complex inquiry process to help them become accomplished problem-solvers.

To facilitate complex inquiry without undermining the nature of student-centered learning, indirect instructions such as prompts, hints, and scripts are used to bring learners' attention to important issues (e.g., what to do next) during the task, or a complex task is decomposed into a set of main actions or key questions. Recent research highlights the importance of making cognitive processes visible in complex problem or task situations. Related work involves the use of mental models for high-order thinking and in-depth learning, such as concept maps representing the relationships between concepts, causal maps representing the relationships of cause and effect, and evidence maps linking evidence with claims or hypotheses. In view of the need for integrating multiple aspects of cognitive processes in exploring a problem, integrated cognitive maps for example by representing the problem-solving process and the knowledge underlying the problem-solving process have shown promising effects (Wang Wu, Kinshuk, Chen, & Spector, 2013; Wu, Wang, Grotzer, Liu, & Johnson, 2016). In this section, we introduce a novel three-dimensional cognitive mapping (3DCM) approach, which makes complex inquiry visible and accessible to students by allowing them to externalize the information on a problem, the subject knowledge underlying the problem, and the hypothesizing and reasoning process involved in exploring the problem in a single image for effective thinking, action, and reflection (Chen, Wang, Dede, & Grotzer, 2017). As shown in Figure 2, the integrated cognitive map consists of three parts: a concept map, a data table, and a reasoning map. The concept map represents the subject knowledge underlying the problem in a set of interrelated concepts. The data table outlines the problem information in a set of key variables and their changes over time. In the reasoning map, each hypothesis is supported ("for") or rejected ("against") by evidence from the problem data or subject knowledge. To examine the root cause of the problem, the hypothesis is further explained by other hypotheses explicating deeper causes of the problem.

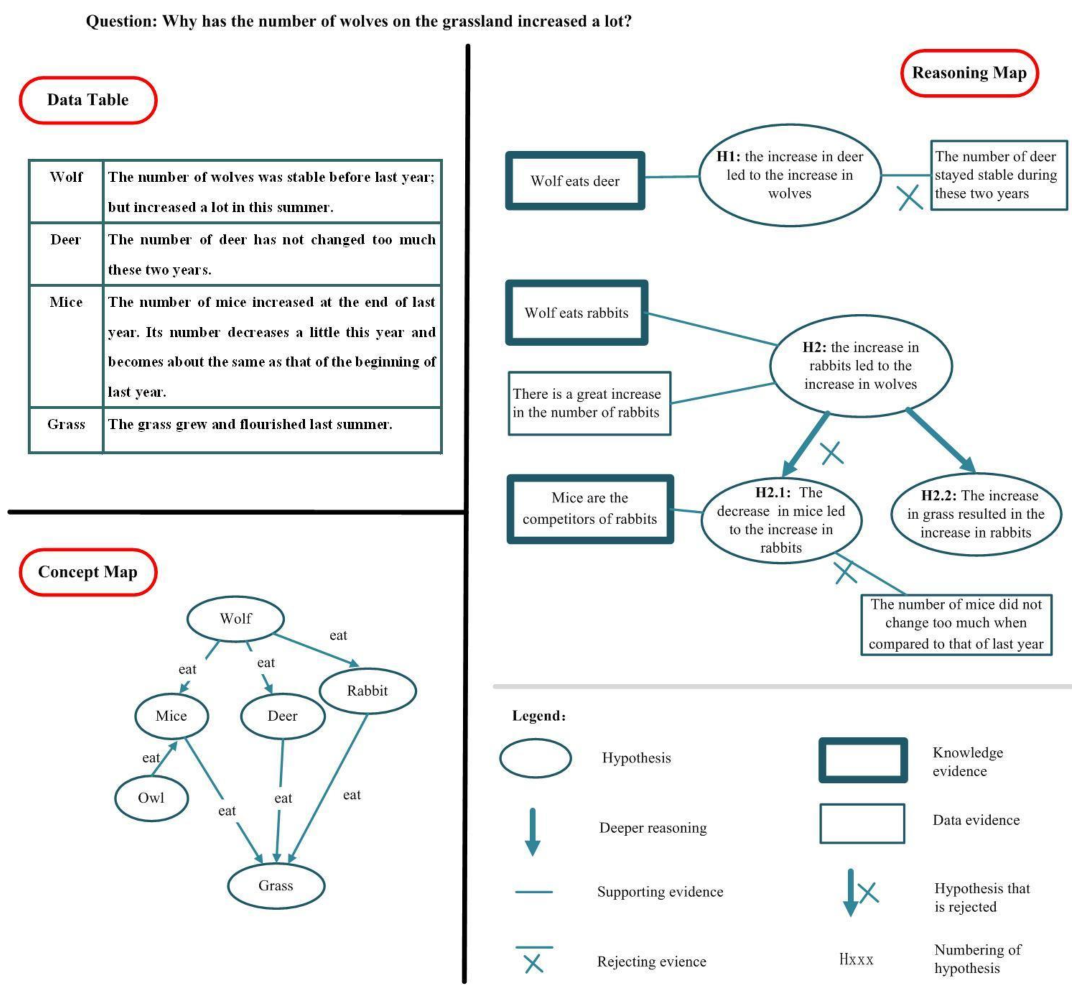

Figure 2. The Three-dimensional cognitive mapping approach

Forty-eight students (24 males and 24 females) from one 11th grade high school class participated in the study. They were classified into three categories of academic ability according to their pre-test scores: high, medium, and low, with each category having 16 students. Students were randomly divided into 16 small groups of 3 (i.e., one high-level, one medium-level, and one low-level student). They explored a fish die-off problem (why many large fish in a pond ecosystem had suddenly died) by performing causal reasoning and construct logical and scientific explanations. To do so, the students interacted with a virtual pond system to collect relevant information and observe changes in multiple variables over time. They discussed and solved the problem in small groups by evaluating and compiling the collected information, formulating and justifying hypotheses, and making conclusions. Students were asked to create a three-dimensional cognitive map to assist their inquiry, and submitted an inquiry report including hypotheses, reasoning, and conclusions.

Pre- and post-knowledge tests were administered to assess students' knowledge of the learning subject. A post-test questionnaire was used to measure students' attitudes toward inquiry learning, anxiety level, and confidence level. The results show that the participants displayed a high level of knowledge gain, positive attitudes, low anxiety, and medium levels of confidence. The interview records reveal that the 3DCM approach provided learners with a holistic view of the inquiry task, and guided them in generating hypotheses step-by-step and developing evidence-based reasoning based on relevant data and knowledge. Moreover, a post-hoc test indicated that the students at a low academic level had acquired significantly more knowledge than either the high-level or medium-level students, thus narrowing the academic gap between low-level, medium-level, and high-level students. Taken together, these findings show promising effects of the 3DCM approach in supporting inquiry learning.

Group Construction of Concept Maps as an Aid to Collaboration

Group construction of concept maps is highly effective for learning. According to a meta-analysis, concept maps have greater learning gains when constructed in groups (d = .96) than when constructed individually (d = .82) or studied individually (d = .37) (Nesbit and Adesope, 2006). The advantage for group construction over individual construction or study may derive from the fact that group construction implicitly combines both of these activities: each learner has both the opportunity to extend the group concept map and the opportunity to study what other members have contributed. The kind of support afforded by group construction appears similar to, but distinct from, the kind of scaffolding provided by so-called expert skeleton concept maps (Novak and Canas, 2006), which are partially specified concept maps with unlabeled nodes and/or edges. Learning gains with skeleton maps appear mixed (Chang, Sun, & Chen, 2001; Wang et al., 2015) and there is some evidence suggesting that skeleton maps assess a different kind of understanding than regularly constructed concept maps (Ruiz-Primo et al., 2001).

Group concept maps conceptually represent the collective individual "mental maps" of the group. Recent work has proposed a framework of "concept landscapes" to analyze collections of individual maps on a shared topic (Muhling, 2017). Two kinds of aggregation are proposed to create concept landscapes. The first is accumulation, a process by which individual maps are related by similarity, shared nodes, or shared edges. A landscape of accumulated maps is perhaps more appropriately considered as a high-dimensional space, e.g., node-space or edge-space, though a low dimensional landscape could also be formed by transforming the map similarity matrix with a technique like multidimensional scaling. The second concept landscape aggregation is called amalgamation. Amalgamation combines individual maps into a single map by merging nodes and edges, weighting them by their frequency across maps, and then pruning the combined map using a technique like thresholding, minimal spanning trees, or the Pathfinder algorithm (Schvaneveldt, 1990).

Group construction of concept maps appears to follow a process of amalgamation, with the important difference that the individual maps are not created before combining. Instead, individual maps are amalgamated incrementally. Through the processes of conversation and shared group map editing, individual mental maps become aligned, nodes and edges are drawn, and less important (or contentious) elements pruned. When considered as amalgamation, group construction of concept maps need not happen synchronously or with a stable group. However, an amalgamation-only view ignores the social context and common ground created by synchronous group construction, and these components would need to be replaced in a group construction paradigm operating asynchronously. Recent work has investigated asynchronous group construction by using a learning companion intelligent agent in place of a human peer (Olney & Cade, 2015). In this work, the learning companion and human student iteratively grow and expand a concept map that is based on previous student interactions. The learning companion effectively replaces the larger group of students by presenting elements of their maps as its own and providing a social presence for the student to engage with. Whether using a learning companion to simulate synchronous group construction is as effective as true synchronous group construction is an ongoing issue for research.

Self-Visualizations as Graphical Representations of Mental Models

Self-visualizations, i.e., graphical representations of one's mental model, have been used in science and computer programming education both as instructional tools and for assessing learners' understanding. For instance, generating a graphical representation during problem solving in conceptual Newtonian Physics plays a similar role as self-explanations, allowing learners to reflect on their understanding of the target concepts as well as enabling the instructor, e.g., a computer-based intelligent tutoring system, to assess learner's understanding and provide hints, for instance, by highlighting elements of the visual representation. That is, the graphical representation is used by the tutor-tutee team to advance their mission of maximal knowledge transfer. We argue that these self-visualizations play a similar role in understanding as self-explanations do. Furthermore, they could help team members understand each other's contributions to, for instance, the team's mission which could be maximal learning or developing a high-quality, i.e., bug-free, complex software product. The latter case offers a unique opportunity to investigate the role of visualizations for collaborative work as large software development projects usually involve very large teams comprising of hundreds or thousands of members with different time, space, and cultural characteristics.

We present next a brief summary of using graphical representation to externalize one's mental models in science learning and computer programming. Examples of such self-visualizations are free-drawings, which allow learners to freely express visually their thinking and understanding, and Control structure diagrams (CSD; Hendrix, Cross II, & Maghsoodloo; 2002). We review briefly previous work on self-visualizations next, that is, we focus on visualizations generated by a target individual as opposed to visualizations generated by an expert through interviewing the individual. Due to space reasons, we do not present visualizations at higher levels of granularity such as system diagrams highlighting the high-level organization of a complex software product. It should be noted that in large software development teams, visualizations play an important role for many aspects of this gargantuan collaborative effort including tracking changes to code, highlighting one's role in the overall team, and training newcomers on the current state of the project (Ellis, Wahid, Danis, & Kellogg, 2007).

The use of visualizations, i.e., free-body diagrams (see Figure 3), as an instructional strategy for improving students' ability to explain and predict Physics situations has been reported by Mualem and Eylon (2010). Mualem and Eylon reported significant learning gains (pretest-posttest) when this strategy was used to coach 9th graders on qualitative problem solving. In another study, Larkin and Simon (1987) showed that translating a propositional problem description into a visual representation is essential in Physics problem solving. Biswas, Leelawong, Schwartz, and Vye (2005) proved the usefulness of using well-structured visual representations (concept maps) in a learning-by-teaching environment. Similarly, visualizations of computer program structure and behavior could help with source code comprehension (Hendrix, Cross II, Maghsoodloo, 2002).

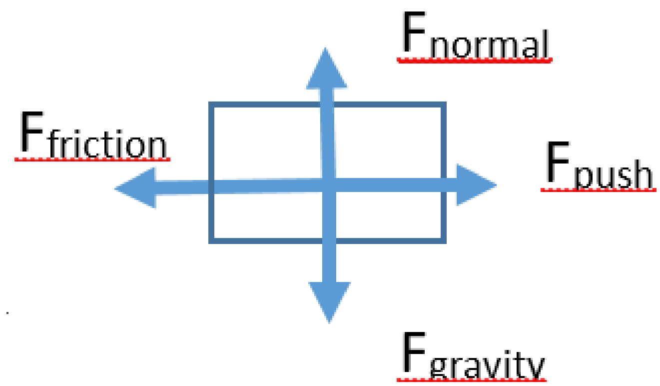

Figure 3. An example of a free-body diagram used in Physics.

Using visual expressions of one's situation model can also be useful for assessing the accuracy of such models. For instance, Chi and colleagues (1994) analyzed mental models from verbal input and drawings. Other research has assessed mental models by asking learners to draw and explain diagrams or visual images that demonstrate an overall function or system (Butcher, 2006; Gadgil et al., 2012).

Control Structure Diagrams (CSDs; Hendrix, Cross II, & Maghsoodloo; 2002) are graphical representations that capture the control structure and modular organization of a computer program. CSDs have the advantage of acting as a companion to source code because CSDs elements are attached to chunks of source code (see Figure 4) as opposed to being a separate representation, which is the case for flowcharts. Hendrix, Cross II, and Maghsoodloo (2002) showed that CSDs are more helpful than other visual representations, e.g., flowcharts, for source code reading and comprehension. The companionship aspect of CSDs with respect to a source code could play a role similar to the use of subgoal labels which have been shown to reduce cognitive load and increase performance while students learn programming (Margulieux, Guzdial, & Catrambone, 2012).

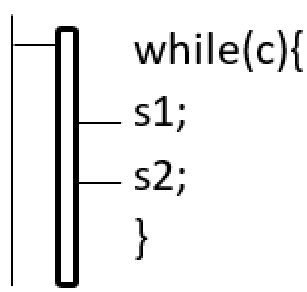

Figure 4. Example of a control structure diagram used in visualizing the organization of computer code.

In sum, self-generated graphical representations of mental models can be used both as an instructional strategy to help one's understanding (Hendrix, Cross II, and Maghsoodloo, 2002; Mualem & Eylon, 2010), for assessing the quality of mental models (Chi et al., 1994; Butcher, 2006; Gadgil et al., 2012), and for expressing a team member's understanding of a larger task that the team must tackle and which can then be used as a starting point to generate a team mental model that encompasses all members' understanding (Ellis, Wahid, Danis, & Kellogg, 2007).

Shared Mental Models for Adaptive Team Training

Cannon-Bowers and Bowers (2011) reason that the most stressful demands on individuals in work/operational environments arise from their participation as a member of a team. These performance demands may be primarily due to the development of teamwork skills that team members must acquire for the team to perform optimally and the emergence of divergent goals within the team, but they may also be due to the complex, and dynamic nature of teamwork and the constant need to adapt to emergent teamwork processes and phenomena (Kozlowski and Ilgen, 2006). Grand et al. (2016) described team dynamics as the modeling of team cognition and shared knowledge of team tasks that underlie team development and thereby affect team learning and performance. To overcome these barriers to learning, the successful team is able to understand goals and construct shared mental models of the processes for teamwork and taskwork.

Shared mental models include organized common knowledge about a system (e.g., instructional domain) that enables individual team members to understand its basic processes and then form predictions and expectations about its future states (Rouse & Morris, 1986). If Intelligent Tutoring Systems (ITSs) are to be effective tools for adaptive team training, Fletcher & Sottilare (2017) advocate a close-coupling of ITS instructional strategies, shared mental models, and teamwork. Sottilare et al. (2017) reinforce this with their findings on the importance of teamwork behaviors, attitudes, and cognition.

In any domain, the successful adaptive team tutor optimizes instruction by adjusting the presentation of content (e.g., text, graphics, and active media like serious games) to maintain team member engagement and thereby optimize learning opportunities within the team. Collaborative graphical activities within adaptive team instruction support the development of or reinforce shared mental models by providing a mechanism leading to better common understanding of the domain, the team, and their learning. These activities may reduce stress and cognitive workload by synchronizing goals and activities, and thereby increase team learning and performance.

Kay, Yacef & Reimann (2007) observed that learners, especially those in leadership roles, found visualizations useful and that a significant number of learners modified their behaviors based on the visualizations provided. Visualizing shared-knowledge awareness, the perception of shared knowledge learners have while working in a collaborative learning context, can also enhance group learning (Collazos, Guerrero, Redondo & Bravo, 2011).

The most effective type of media to support the development of shared mental models and improve team performance may depend on the type of activity (e.g., team taskwork, collaborative learning, or collaborative problem solving) in which the team is engaged. During taskwork activities, graphics that provide the status of team performance or achievement (e.g., dashboards) can level understanding within the team leading to better performance. Widgets within dashboards that represent leaderboards, activity streams, and concept maps are common and useful. During collaborative learning activities, graphics that model concepts or processes (e.g., free body diagrams) can reinforce individual learning or identify shortfalls in knowledge, misconceptions or diverging objectives of team members. In attempting to collaboratively solve problems, graphics that visualize data or allow learners to share and vet information are also valuable.

Conclusion

The graphical supports described in this chapter (concept maps, 3-dimensional cognitive mapping, and self-visualizations) have proven to be effective vehicles for the collaborative construction of mental models. Each fulfills the necessary condition of organized common knowledge about a system (e.g., instructional domain) that enables individual team members to understand its basic processes and then form predictions and expectations about its future states). As advances in technology enable increasingly sophisticated types of visual representations, such as virtual and mixed realities (Liu, Dede, Huang, & Richards, 2017), insights from the graphical supports described here will aid in designing effective vehicles for collaboration.

In GIFT, the Domain Course file and the Domain Knowledge file are good components in which to implement graphical/visual representations for shared mental models. Digital tools for creating individual and group graphical supports have the advantage of providing a logfile record of the steps involved in producing these mental models, so that both instructors and students can review the processes of creation by individuals and synthesis/collaboration by the group. This is not only valuable in producing a shared mental model, but also in elucidating strengths and weaknesses of the collaborative actions involved.

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