Toward a Taxonomy of Team Performance Visualization Tools

Zachari Swiecki, University of Wisconsin, Madison, swiecki@wisc.edu
David Williamson Shaffer, University of Wisconsin, Madison, dws@education.wisc.edu

Abstract: Research on teams has become increasingly important due in part to the status of collaborative problem solving as a vital 21st century skill. Much of this research has focused on factors that affect team processes and outcomes, such as the use of team performance visualization tools. Such tools are also valuable to researchers who make inferences from team data or educators who assess teams and plan interventions. This variety of users suggests that studying these tools requires a user-centered approach focusing on affordance relationships. In this paper, we use Epistemic Network Analysis to create a visual representation of the space of affordance relationships for extant team performance visualization tools. We use this space to compare tools, and to demonstrate empirically the dimensions along which they differ. These dimensions suggest a preliminary taxonomy of tools in terms of their affordance relationships for different users.

Introduction

Teams are collections of individuals who work together to learn, solve problems, make decisions, and design products. Recently, research on teams has become increasingly prevalent due to their ubiquity and growing importance in society. Moreover, collaborative problem solving—and collaboration more generally—has been recognized as a vital 21st century skill (Griffin & Care, 2014). Much of the extant research on teams has focused on factors that affect *team performance*, which may refer to either team outcomes or the processes teams take to achieve those outcomes. One such factor is how tool use by teams affects their performance. In particular, a growing body of research has focused on how *visualizations* of team performances affect team outcomes and processes (e.g., Fiore & Wiltshire, 2016; Janssen & Bodemer, 2013).

Team performance visualizations are not only important for teams, however. Given the complexity and volume of team interaction data that can be collected, visualizations also play an important role in how researchers investigate teams and how educators monitor and assess them. This variety of users, and their differing goals, suggests that those who study team performance visualizations should take a user-centered approach. Such an approach would consider both the properties of visualization tools and those who use them—in other words, it would consider the *affordance relationships* that exist between these tools and their users (Norman, 2013).

Several prior studies have investigated features of team performance visualization tools, such as awareness tools and dashboards (e.g., Bodily & Verbert, 2017; Janssen & Bodemer, 2013; Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). However, these studies are lacking either because they do not focus on team data specifically, they ignore certain user groups, they ignore large classes of tools, or they do not consider how the affordances of tools relate to one another. To address this gap, we conducted an empirical investigation of extant team performance visualization tools and derived a preliminary taxonomy in terms of their affordance relationships with three user groups: teams, researchers, and educators. Such a taxonomy should help to better distinguish tools and provide guidance to different users. To analyze and visualize our data, we used Epistemic Network Analysis, or ENA, (Shaffer, Collier, & Ruis, 2016) a method for analyzing the connections between features of interest in data, and thus a powerful technique for investigating the collections of affordances that exist in tools.

Theory

It is widely recognized that the tools we use affect how we think and act (Hutchins, 1995; Vygotsky, 1978). Several fields, including the learning sciences, social psychology, and organizational psychology, have investigated tools in relation to teams. Much of this work has focused on the effects of different visualization tools on team performance. For example, those who study Computer Supported Collaborative Work have investigated how shared representations, such as digital whiteboards, affect team performance (Fiore & Wiltshire, 2016). And in Computer Supported Collaborative Learning, researchers have studied how different visualization tools affect communication (Munneke, Andriessen, Kanselaar, & Kirschner, 2007), the construction of joint problem spaces (Roschelle & Teasley, 1995), and participation (Janssen & Bodemer, 2013).

Team performance visualization tools—and tools more generally—affect teams through what Norman (2013) calls *affordances*, or particular relationships between the properties of tools and the capabilities of their users. Several authors have investigated the affordance relationships that exist between team performance visualization tools and teams. For example, Janssen and Boedmer (2013) argue that *cognitive group awareness* tools, which provide information about the distribution of team *knowledge*, help to coordinate social and cognitive activity by facilitating communication and the development of shared mental models. Similarly, *social group awareness* tools, which provide information about the *activities* of team members such as communication levels or contributions to tasks, help teams to coordinate action and information in situations where they cannot directly see one another's behavior. These awareness tools may also allow team members to *identify* and directly compare their performance to that of their teammates, creating opportunities for social comparison. Other tools may occlude individual contributions, instead showing metrics of team performance only at the team level (Kimmerle & Cress, 2008; Kimmerle, Cress, & Hesse, 2007).

While it is clear that tools affect how teams perform, they also affect how researchers measure team performance. To understand and make claims about teams, researchers design assessments to collect evidence that warrant those claims (Mislevy, 1996). However, teams are dynamic and complex systems. They have multi-level structure, individuals interact with one another and with tools, and these interactions change over time. The combination of these features means that evidence elicited from teams is both vast and complex. For example, many researchers study teams who work together in virtual environments. Such environments log data on interactions within the environment, including mouse clicks, verbal or chat communications, and product submissions. The complexity of these data has led many researchers to use visualization tools in order to make meaning from the evidence they collect. For example, researchers have used a variety of *network* tools to visualize both the *structure* of team interactions and the *semantic* content of those interactions (e.g., Dawson, Tan, & McWilliam, 2011; Sha, Teplovs, & van Aalst, 2010). *Temporal* visualization tools, such as CORDTRA, have been used to analyze the sequence and simultaneity of team interactions (Hmelo-Silver, Jordan, Liu, & Chernobilsky, 2011). And *dependency* visualizations, such as those derived from state transitions, Markov models, and process models, have been used to investigate the likelihood that team actions follow or depend on one another (Reimann, P., Frerejean, J., & Thompson, K., 2009).

Furthermore, given the volume and complexity of team data, educators have come to rely on tools that convey information about teams succinctly in real-time. Consequently, learning analytic *dashboards* have been designed to provide educators with information about team activity and performance in condensed views (Verbert et al., 2013). Many of these dashboards, such as the Process Tab (Shaffer, 2017) , which uses network diagrams to represent the connections teams make between concepts as they collaborate, allow educators to access the data underlying the visualizations to see more *detailed* information on demand.

Each of the properties described above—knowledge, activity, member identification, structure, semantics, temporality, dependence, and details—are features of team performance visualization tools that afford different actions for different users. Teams use these affordances to facilitate communication and compare their performance; researchers use them to test hypotheses and build theories; and educators use them to assess students or plan interventions. Importantly, the affordances of any given tool do not exist in isolation. For example, concept maps, one kind of cognitive group awareness tool, represent information about team knowledge and information about the structure of that knowledge—that is, how knowledge components relate to one another. In addition, dashboards typically contain a variety of visualizations of team performance. One dashboard, Collaid (Martinez Maldonado, Kay, Yacef, & Schwendimann, 2012), contains at least five visualizations, including radar graphs, pie charts, and time series, which simultaneously provide information about how team activities change over time. In other words, team performance visualization tools are interactive systems in which different affordances relate to and affect one another. Thus, understanding and describing the affordance relationships between different tools and their users requires a method of analysis focused on how affordances connect to one another. One such method is Epistemic Network Analysis, or ENA (Shaffer, Collier, & Ruis, 2016).

ENA measures connections among relevant features in data and represents those connections as networks. ENA was developed to model cognitive networks, or networks that represent associations between elements of complex thinking. This method has been used to study the patterns of connections that teams of learners make as they solve problems in simulations of professional practice (e.g., Shaffer et al., 2016). Thus, ENA itself is a team performance visualization tool. However, ENA is also a general method for investigating data where complex patterns of relationships are thought to exist. In this study, we use ENA to create a visual representation of the space of affordances for extant team performance visualization tools. Using this space, we compare tools, and also demonstrate empirically the dimensions along which they differ.

Several prior studies have investigated the affordances of team visualization tools for different user groups. However, each case has important limitations. For example, Verbert and colleagues (2013) conducted a review of over 20 learning analytics dashboards. These authors classified each dashboard according features such as target user (teacher or student) and data source (social interaction, time spent, and so on). This review accounted for two kinds of users; however, it was limited to one particular kind of visualization tool and did not specifically target dashboards that represent team performance data.

Taking a team focus, Janssen and Bodemer (2013) reviewed the literature on group awareness tools. These authors identified the kind of data represented by each tool, how the data was collected, and characteristics of the visualizations used. This work explicitly looked at tools designed for teams as the target user, and it considered several affordances of these tools for teams. However, other aspects of the visualizations considered tended to focus only on surface level properties and not the interactions they afforded. Moreover, this review did not consider tools designed for researchers or educators.

Each study above contributes toward understanding the affordance relationships between team performance visualization tools and their users. However, they either ignore certain users, ignore large classes of tools, or do not focus on teams. Work discussing team performance visualization tools for researches is also deficient in that it often only implicitly demonstrates their affordances. That is, this work shows what these tools can do in terms of providing insights into team performance or building theory, but they do not explicitly discuss the properties of the visualizations that make these insights possible. And while some work is more explicit in this regard (e.g., Siebert-Evenstone et al., 2016), it is rare that authors discuss a variety of these visualizations together in one place.

In this paper, we address the limitations of prior work by conducting an empirical investigation of the affordances of extant team performance visualization tools. In particular, we examine the literature on these tools and ask the following two research questions: (1) what are the affordances of extant tools? And, (2) how do these affordances differ across user groups? This analysis provides some first steps toward a taxonomy of tools that should guide future work and help users select appropriate tools given their goals.

Methods

Data

To address the research questions above, we first collected a representative sample of papers that described team performance visualization tools and their affordances. To collect this sample, we consulted a panel of three domain experts who have extensive experience in measuring and visualizing team performance. These experts suggested specific papers in which team performance visualization tools were described, as well as topics for a literature search. Using these papers, their citations, and literature search topics, we collected a sample of 41 papers and book chapters, which were reviewed and approved by the expert panel. From this sample, we identified 48 team performance visualization tools for this study.

Coding

Two raters classified the tools described in each paper into one of six types: (1) social group awareness tools, (2) cognitive group awareness tools, (3) dashboards, (4) networks, (5) dependency visualizations, and (6) temporal visualizations. The distribution of tools by type is shown in table 1.

Table 1: Counts of team performance visualization tools by type

Type	Count
Social Group Awareness	17
Cognitive Group Awareness	11
Dashboards	11
Networks	4
Dependency Visualizations	3
Temporal Visualizations	2

Next, the two raters coded each tool for their intended user and affordances. The user categories included four codes: (1) team, (2) educator, (3) team and educator, and (4) researcher. Tools coded for the first three categories were described in papers that explicitly mentioned the end user of the tool. Tools coded for the researcher category either did not mention the end user of the tool, or only reported on the analysis of team performance data using a given tool. In total, 31 tools were coded for teams as the intended user, 3 for educators, 5 for teams and educators, and 9 for researchers. We developed the visualization affordance codes from a grounded analysis (Glaser & Strauss, 1967) of the data. We define these codes in table 2.

Table 2: Visualization affordance codes

Code	Definition	Example
Activity	Represents information about the activity or participation of the team, e.g., how much they are communicating or contributing to the task.	Collaid dashboard: Martinez-Maldano et al., 2012
Knowledge	Represents information about the knowledge, opinions, or understandings held by the team.	Concept maps: Engelmann & Hesse 2011
Structure	Represents the structure of teams, their interactions, or their knowledge, e.g., subgroups, communication patterns, or connections between concepts.	Social network graphs: Dawson & McWilliam, 2011
Semantics	Represents the content of team interactions or knowledge—rather than, or in addition to—quantity or structure.	KSV: Sha et al., 2010.
Dependence	Represents information about how team actions depend on other team actions, e.g., the likelihood that one action follows another.	Dependency graphs: Reimann et al., 2009.
Temporality	Represents information about the simultaneity, sequence, or change of team actions or knowledge over time.	CORDTRA: Hmelo-Silver et al., 2011.
Member Identification	Contributions from each individual team member are identifiable within a single visualization in the tool.	Social awareness tool: Kimmerle et al., 2007.
Details	Allows users to access the data underlying the visualization.	Process Tab: Shaffer, 2017.

Two raters coded each visualization tool for the type, user, and affordance codes described above. Given the relatively small sample size, both raters coded the entire data set together, resolving differences as they coded, and arriving at a single decision for each code. Thus, the kappa statistic for this coding was 1.

Analysis

After coding, we analyzed the data using ENA. ENA measures connections among codes in data and represents them as networks. In this study, we used ENA to construct network models for each of the 48 team performance visualization tools. Here, the units of analysis are the tools, the network nodes correspond to the affordance codes in table 2, and a network for a given tool represents its collection of affordances.

The process of creating ENA models is described in more detail elsewhere (Shaffer et al., 2016), but in brief, ENA creates adjacency matrices for each unit of analysis that quantify the co-occurrences of codes within the unit. Next, the adjacency matrices are normalized and represented as vectors in a high dimensional space, where each dimension corresponds to a co-occurrence of codes. A dimensional reduction via singular value decomposition is then performed to project the vector for each unit of analysis into a lower dimensional space that maximizes the variance accounted for in the data. Finally, the nodes of the networks are placed in the space using an optimization algorithm such that the center of mass for a given unit's network closely corresponds to that unit's location in the lower dimensional space. Importantly, these nodes placements are fixed, meaning that the nodes of each network are in the same place for all units in the analysis. This fixed set of node positions allows for meaningful comparisons between units in terms of their connection patterns and allows us meaningfully interpret the dimensions of the space.

The final result is two coordinated representations for each unit of analysis: (1) a *plotted point,* which represents the location of that unit's network in the low-dimensional space, and (2) a weighted network graph. Because the location of any plotted point corresponds to the center of mass of its corresponding network, we can use the weighting of the network to explain that point's location. Thus, plotted points located on the right hand side of the space will have networks whose strongest, or most heavily weighted, connections appear on the right. Similarly, plotted points located on the left will have networks whose strongest connections appear on the left, and so on. Using ENA, we can also group plotted points by metadata and calculate the mean position in the space for a group. This mean can be plotted in the same metric space and has a corresponding network graph which represents the average connections between codes for that group. In this analysis, we grouped the visualization tools in two ways: by type of tool (table 1) and by user. In both cases, to make comparisons between groups we used their mean position in the space, their mean network diagrams, and network difference graphs, which subtract the edge weights of two networks to show the strongest connections in each group.

Results

In this study, we used ENA to investigate (1) the affordances of extant team performance visualization tools and (2) how those affordances differ across user groups. With regard to the first, in the figures below we see the results of the ENA analysis for the six types of tools described above. Fig 1 shows the mean plotted points (colored squares) for each type of tool, as well as the overall mean point, in ENA space. In the figure, we have also included the network for the overall mean, which helps to interpret the dimensions of the space. For the mean network in figure 1, the thickness and saturation of a given connection reflects the average number of tools coded for both codes defining the connection.

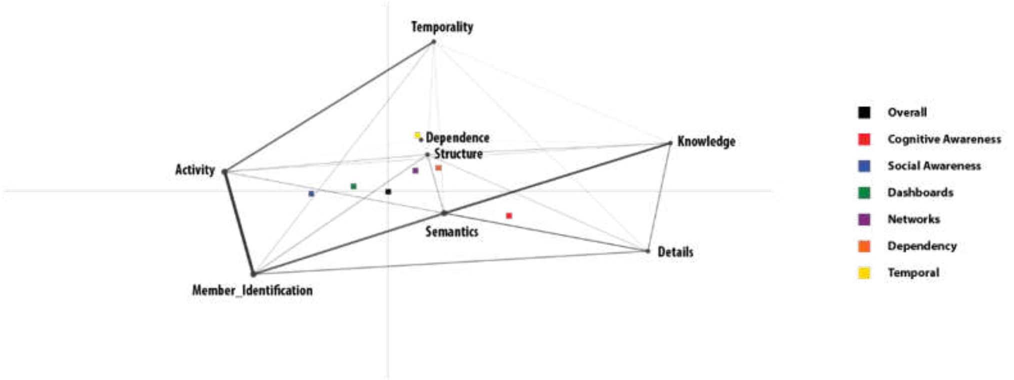

Fig 1. Mean plotted points and overall mean network for the six tool types. Legend on the right.

Because of the relationship between network representations and plotted points in ENA, we can use this network layout to interpret the dimensions of the space, and in turn, the meaning of each point's location. Thus, the Y dimension separates visualization tools in terms of their focus on more complex data transformations, such as showing temporality, dependence, or structure (top), versus less complex transformations like showing individual contributions or underlying data (bottom). On the other hand, the X dimension separates visualization tools in terms of their focus on social information about each team member, such as their activity levels (left), versus more cognitive information, such as the knowledge held by the team (right).

The interpretation of the dimensions above helps to explain the location of tools in the space, as well as the differences between them. For example, in the figure, we see that the mean location of social and cognitive awareness tools in the space is quite different. To highlight this difference, in figure 2 we constructed a difference graph showing which connections, on average, are stronger in one kind of tool versus the other. In particular, this graph shows that cognitive awareness tools (red) are toward the right and lower down in the space due to their focus on representing team knowledge, underlying data, and the contributions of all members on the team. Contrastingly, social awareness tools (blue) are toward the left and higher up due to their focus on representing the social activity of each team member and how that activity changes over time.

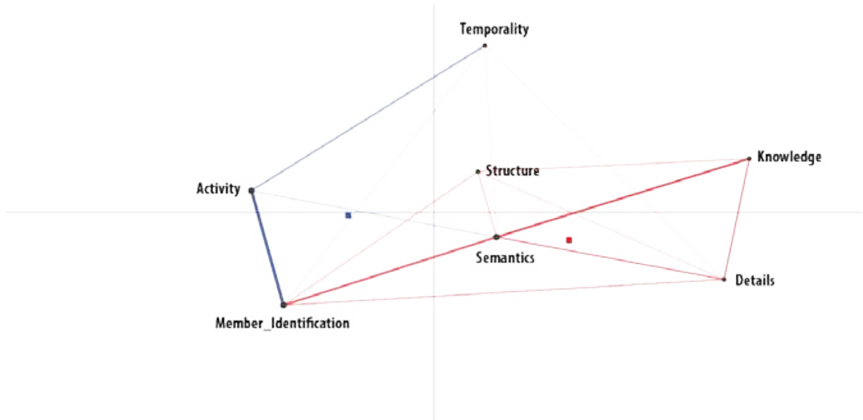

Fig 2. Network difference graph for social (blue) and cognitive (red) awareness tools.

Page limitations do not allow us to include the network diagrams like those in figures 2 for each type of tool; however, the defining affordances of each tool type can be inferred from the location of their mean plotted points and the interpretation of dimensions described above. For a more detailed account, we examined the separate networks for each type of tool and found that network visualizations (purple, figure 1) are defined by more complex representations of the structure and semantics of team activities and knowledge. Similarly, dependency visualizations (in orange) are defined by the representation of those same features, with the addition of information about how team activities or knowledge components depend on one another. Temporal visualizations are defined by representations of temporality and the semantic content of team activity and knowledge. Finally, dashboards are defined by representations of how the activity of team members change over time.

With regard to our second research question, figure 4 below shows the results of the ENA analysis of visualization tools grouped by their intended user. Thus, the colored squares in this figure correspond to the mean plotted point positions of tools grouped by user, whereas in figure 1 above, the colored squares correspond to the mean plotted point positons of the tools grouped by visualization type. Here again, we include the overall mean network diagram to aid in interpretation. Because only the groupings of tools have changed, the interpretation of the dimensions remains the same as above.

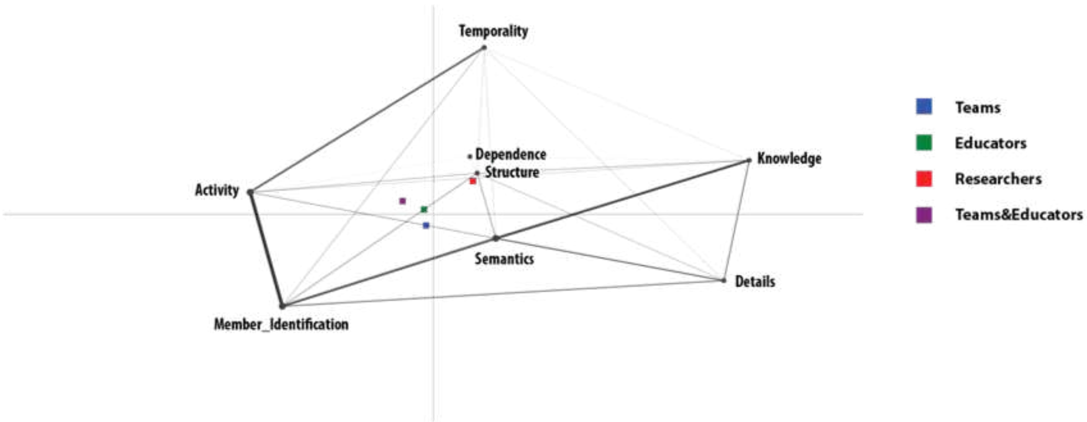

Fig 3. Mean plotted points and overall mean network for tools by user. Legend on the right.

Figure 3 shows that, on average, visualization tools designed for teams (in blue), focus on representing information about the activity and knowledge of each individual on the team, as well as the data underlying the visualizations. On the other hand, tools designed for use by researchers (in red) focus on representing more complex information such as temporality, structure, and dependence.

Tools designed for educators or teams and educators (green and purple respectively) are located below and to the left of researcher tools, meaning that they focus more on the activity of team members and underlying data, rather than more complex team performance data. However, their location on the Y axis is higher than tools designed for teams, meaning that they focus relatively more on complex data than team tools, on average.

Discussion

The ENA analysis above suggests a preliminary taxonomy of team performance visualization tools in terms of their affordances. The dimensions of the ENA space distinguish between those tools that focus on representations of social versus cognitive information on the X axis, and those tools that focus on more or less complex transformations of team performance data on the Y axis. These dimensions define four broad categories with which we can classify the different tools: complex/cognitive, complex/social, simple/social, simple/cognitive. Thus on average, network, dependency, and temporal visualizations fall into the complex/cognitive category; dashboards fall into the complex/social category; social awareness tools into the simple/social category (though just barely); and cognitive awareness tools into the simple/cognitive category. These same categories also apply to the tools when grouped by user: researcher tools tend to be complex/cognitive; educator tools, complex/social; educator and team tools, complex/social; and team tools, simple/social.

The taxonomy described above has at least two important implications, one practical and one theoretical. First, it allows potential users to make clear distinctions between tools in terms of their affordances. This taxonomy could help users to distinguish between broad types of visualization tools such as temporal versus network tools or to make more fine-grained comparisons between individual tools. These distinctions may also help users understand which tools complement one another, and guide their decisions about which tools to use given their goals. For example, researchers interested in visualizing complex cognitive information about teams over time may find temporal visualizations useful. However, if they are also interested in the structure of team cognition, or how team cognitive components depend on one another, then they may want to supplement their analyses with network or dependency tools.

Second, this taxonomy suggests potential areas of further inquiry and visualization tool development. For example, the discrepancy between tools designed for researchers and those designed for teams suggests that more complex and cognitively focused tools have yet to be developed for teams. A potential explanation for the lack of more complex tools for teams may have to do with the *constraints* associated with them. Just as tools have affordances that make certain interactions possible, their constraints place limits on those interactions. The researcher visualization tools are constrained in the sense that they may require more knowledge or expertise to understand, and more time to interpret. Teams that lack this knowledge and time may not benefit from such tools unless they are carefully designed for their contexts. For now, the effect of such tools on team performance remains an open question.

This study has several obvious limitations. First, our data selection procedure was limited in that it relied on the suggestions of a small panel of experts. Although these selections were supplemented by citation and literature searches, a more systematic search of the literature would likely have added to our sample. Future work will explore more systematic data selection methods. Second, in the majority of cases, our coding process was limited to investigating descriptions or images of the visualization tools rather than the tools themselves. Thus, it is possible that some important features were missed if they were not clearly described in their write-ups. Finally, the sample sizes for some types of visualization tools, such as temporal tools, were relatively small. The normalization feature of ENA should mitigate such differences in sample size; however, future work will target literature searches around tools that were less represented here. Despite these limitations, this work provides a preliminary taxonomy of team performance visualization tools based on an empirical analysis. Investigating more tools will test the stability of the ENA model and taxonomy presented here, and should improve its utility for teams, educators, and researchers.

References

Barron, B. (2003). When Smart Groups Fail. *Journal of the Learning Sciences*, *12*(3), 307–359.

Bodily, R., & Verbert, K. (2017). Review of research on student-facing learning analytics dashboards and educational recommender systems. *IEEE Transactions on Learning Technologies*, 1–1.

Dawson, S., Tan, J. P.-L., & McWilliam, E. (2011). Measuring creative potential: Using social network analysis to monitor a learners' creative capacity.

Engelmann, T., & Hesse, F. W. (2011). Fostering sharing of unshared knowledge by having access to the collaborators' meta-knowledge structures. *Computers in Human Behavior*, *27*(6), 2078–2087.

Fiore, S. M., & Wiltshire, T. J. (2016). Technology as Teammate: Examining the Role of External Cognition in Support of Team Cognitive Processes. *Frontiers in Psychology*, *7*.

Glaser, B. G., & Strauss, A. L. (1967). *The discovery of grounded theory: Strategies for qualitative research*. Aldine de Gruyter.

Griffin, P., & Care, E. (2014). *Assessment and teaching of 21st century skills: Methods and approach*. Springer.

Hmelo-Silver, C. E., Jordan, R., Liu, L., & Chernobilsky, E. (2011). Representational tools for understanding complex computer-supported collaborative learning environments (pp. 83–106). Springer.

Hutchins, E. (1995). *Cognition in the wild*. Cambridge, MA: MIT Press.

Janssen, J., & Bodemer, D. (2013). Coordinated Computer-Supported Collaborative Learning: Awareness and Awareness Tools. *Educational Psychologist*, *48*(1), 40–55.

Kimmerle, J., & Cress, U. (2008). Group awareness and self-presentation in computer-supported information exchange. *International Journal of Computer-Supported Collaborative Learning*, *3*(1), 85–97.

Kimmerle, J., Cress, U., & Hesse, F. W. (2007). An interactional perspective on group awareness: Alleviating the information-exchange dilemma (for everybody?). *International Journal of Human-Computer Studies*, *65*(11), 899–910.

Martinez Maldonado, R., Kay, J., Yacef, K., & Schwendimann, B. (2012). An Interactive Teacher's Dashboard for Monitoring Groups in a Multi-tabletop Learning Environment. In S. A. Cerri, W. J. Clancey, G. Papadourakis, & K. Panourgia (Eds.), *Intelligent Tutoring Systems* (Vol. 7315, pp. 482–492). Berlin, Heidelberg: Springer Berlin Heidelberg.

Mislevy, R. (1996). *Evidence and inference in educational assessment*. Los Angeles: National Center for Research on Evaluation, Standards, and Student Testing.
Munneke, L., Andriessen, J., Kanselaar, G., & Kirschner, P. (2007). Supporting interactive argumentation: Influence of representational tools on discussing a wicked problem. *Computers in Human Behavior*, *23*(3), 1072–1088.
Norman, D. (2013). *The design of everyday things: Revised and expanded edition*. Basic Books (AZ).
OECD. (2017). PISA 2015 collaborative problem‑solving framework. In *PISA* (pp. 131–188). Organisation for Economic Co-operation and Development. Retrieved from http://www.oecd-ilibrary.org/content/chapter/9789264281820-8-en
Reimann, P., Frerejean, J., & Thompson, K. (2009). Using process mining to identify models of group decision making in chat data. In *Proceedings of the 9th international conference on Computer supported collaborative learning-Volume 1* (pp. 98–107). International Society of the Learning Sciences.
Roschelle, J., & Teasley, S. D. (1995). The Construction of Shared Knowledge in Collaborative Problem Solving. In C. O'Malley (Ed.), *Computer Supported Collaborative Learning* (pp. 69–97). Berlin, Heidelberg: Springer Berlin Heidelberg.
Sha, L., Teplovs, C., & van Aalst, J. (2010). A visualization of group cognition: Semantic network analysis of a CSCL community. In *Proceedings of the 9th International Conference of the Learning Sciences-Volume 1* (pp. 929–936). International Society of the Learning Sciences.
Shaffer, D. W. (2017). *Quantitative ethnography*. Madison, WI: Cathcart Press.
Shaffer, D. W., Collier, W., & Ruis, A. R. (2016). A tutorial on epistemic network analysis: Analyzing the structure of connections in cognitive, social, and interaction data. *Journal of Learning Analytics*, *3*(3), 9–45.
Siebert-Evenstone, A.L., Arastoopour Irgens, G., Collier, W., Swiecki, Z., Ruis, A.R., & Shaffer, D.W. (2017). In search of conversational grain size: Modelling semantic structure using moving stanza windows. *Journal of Learning Analytics*, *4*(3), 123–139.
Verbert, K., Duval, E., Klerkx, J., Govaerts, S., & Santos, J. L. (2013). Learning analytics dashboard applications. *American Behavioral Scientist*, *57*(10), 1500–1509.
Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes* (14th ed.). Cambridge, MA: Harvard University Press.

Acknowledgments

This work was funded in part by the National Science Foundation (DRL-0918409, DRL-0946372, DRL-1247262, DRL-1418288, DRL-1661036, DRL-1713110, DUE-0919347, DUE-1225885, EEC-1232656, EEC-1340402, REC-0347000), the MacArthur Foundation, the Spencer Foundation, the Wisconsin Alumni Research Foundation, and the Office of the Vice Chancellor for Research and Graduate Education at the University of Wisconsin-Madison. The opinions, findings, and conclusions do not reflect the views of the funding agencies, cooperating institutions, or other individuals.