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ABSTRACT

The goal of this paper is to present several methods of visualizing student activity and collaboration in problem-based learning (PBL) in ways that can augment understanding of the complexity within PBL classrooms as well as to provide insights into the use of specific visual representations to address research questions in PBL. Grounded in sociocultural theory, we consider these representations to be an aid to mediate researchers' interpretation of the multiple data streams generated in PBL. For quantitative analysis, we introduce social network system (SNA), structural equation model (SEM) and path modeling. In terms of qualitative analysis, we exhibit chronologically-ordered representation of discourse and tool-related activity (CORDTRA), event maps, and spatial representations of physical activity. By reviewing articles that utilized these representations in PBL, we present several examples of how these visualizations were helpful in interpreting complex data and illuminating how students learn in PBL and other forms of collaborative inquiry. Although such visual representation methods enable us to visualize and trace complex dynamics and communicate findings with readers, they are not self-explanatory. We further discuss potential pitfalls of using visualizations and how to fully take advantage of those tools in PBL research studies.

Keywords: visual representation, methods for visualization, research methods, problem-based learning, collaborative inquiry

Visual Representations for Studying Collaborative Inquiry

From sociocultural perspectives, learning is socially situated, highly contextual, and a dynamic social process (Danish & Gresalfi, 2018; Palincsar, 1998). This process is mediated by tools in an ecological context (Cole, 1996). Therefore, it is critical to understand how learners socially construct their understanding through interaction with others and tools in multifaceted ways. Visual representations enable us to convey such complex information in a recognizable form that can be easily interpreted. Larkin and Simon (1987) also argue that visual representations, such as a diagram, are often much easier to understand than verbal representations of the same content and can make it easier to construe complex patterns. Given these affordances, it is little wonder that educational researchers have widely used visual representations to analyze data and communicate their findings with others.

Research in problem-based learning (PBL) environments requires understanding how students learn in this complex environment. These are best understood through multiple data sources to understand this complex activity system where analyzing and integrating multiple sources of data is crucial (Hmelo-Silver et al., 2008). To address such research questions, studies in this field seek to capture the chronology of learners' tool use or collaboration, which mediates their learning (Derry et al., 2006). Researchers also examine what and how patterns of interactions with others and tools support their meaning-making process or certain learning outcomes (Bridges, Chan, et al., 2020; Green & Bridges, 2018). However, simple coding, counting, and aggregation or basic statistics are likely to flatten the complexity of the PBL contexts, and thus might not be able to comprehensively capture learning as a holistic and dynamic process (Hmelo-Silver et al., 2011). As a result, research studies implemented in the context of complex learning environments such as PBL and computer-supported collaborative learning (CSCL) have utilized diverse visual representation methods to capture and apprehend how the complex learning contexts and tools mediate students' learning. For instance, previous research studies have investigated interaction patterns (Li et al., 2022; Martinez, 2003; Tao & Zhang, 2021) and effectiveness of different social structures in CSCL contexts (Zhang et al., 2009) with social network analysis (SNA). Additionally, Bridges, Hmelo-Silver, et al. (2020) investigated how learning multimodal artifacts mediated learners' knowledge building with an event map and a spatial representation of physical activities. Previous literature also examined how learners' discourse, non-verbal expressions, and tool use evolved over time with CORDTRA (chronologically-ordered representation of discourse and tool-related activity) diagrams (Derry et al., 2006; Hmelo-Silver, 2003). In sum, these visual representation methods are important tools for understanding learning in PBL.

In this article, we ground our work in sociocultural theory by viewing learning as a socially situated process that takes place in a systematic environment, where learners socially co-construct meanings by interacting with others, learning content, and mediating tools. To study these interactions and engagement, we rely on visual representations to help researchers interpret the multiple data streams generated in PBL, including videos, computer log data, gestures, and student artifacts. We will present several examples of how these visualizations were helpful in interpreting complex data and illuminating how students learn in PBL and other forms of collaborative inquiry. Specifically, the current paper aims to: (a) review the visual representations that have been widely used in PBL including CORDTRA, SNA, structural equation model (SEM), event maps, and spatial representations of physical activity; (b) provide insights into the use of specific visual representations to address research questions in PBL, and (c) discuss potential pitfalls for the better use of visual representation methods. We begin by briefly illustrating the history of visualizations in PBL research and the research questions that particular visual representation methods can answer. Then, we introduce each visual representation method that supports our understanding of complex learning processes and environments. Lastly, we discuss potential pitfalls and takeaways of using each method and provide insights into their appropriate use.

History of Visualizations in PBL Research and Development

In PBL, new technologies have been incorporated into classrooms to promote diverse learning experiences and maximize teachers' capacity to facilitate learning. Researchers have collected a wide variety of data to accurately portray the complexity of technology-mediated learning environments and understand the interactions that take place between teachers and students, students and learning technologies they utilize, and teachers and technologies used to orchestrate learning (Dillenbourg, 2013; Sharples, 2013). Visual representations or visualizations can be used for simplifying difficult-to-comprehend information, illuminating patterns and complex relationships, and enhancing overall readability and accessibility of data (Munzner, 2015; Ware, 2019). To understand PBL, especially in technology-rich learning environments, a growing number of researchers have made wide use of visualizations in research to support their data analysis and communicate findings (Hmelo-Silver & Jeong, 2021; Janssen et al., 2007; Vieira et al., 2018). With visualizations, researchers can reveal collaboration patterns and multidimensional relationships that may not be evident in raw data, especially when examining large quantities of unstructured data.

PBL researchers face challenges in understanding and analyzing data when translating PBL into technology-mediated complex learning environments, particularly when scaling up PBL models into large classrooms. PBL researchers need to understand many groups' learning process and teacher facilitation, but they also must identify the interactions among different data streams. Due to such challenges, visualizations offer promise in understanding complex learning environments.

Research Studies with Visual Representation Methods

Research studies from both sociocultural and cognitive approaches to PBL have sought to address a broad range of questions and provided researchers with a greater understanding of the various components of PBL using a variety of representational tools. Among these visualization tools, some are more suitable for research involving quantitative methods, such as the identification of latent variables within complex systems, while others are better suited for analyzing rich qualitative data and uncovering connections between different elements.

Quantitative Methods for Visual Representation

Social networks analysis (SNA), structural equation modeling (SEM), and path modeling in general are commonly used with quantitative methods when trying to explore quantitative relationships between the variables within a complex learning system. Drawing from Carolan (2013), social network is described as a group of actors, including individuals (e.g., learners and teachers), resources, and ideas, and relations between the actors. SNA focuses on mapping the relationships between actors and how they are related to each other (Shum & Ferguson, 2012). It is useful for understanding the social structure and the patterns or properties of relations among the actors (Carolan, 2013; Scott, 1991). SEM is a statistical technique that can model the relationships between different variables. It is particularly useful to understand the underlying associations between these variables, such as expertise use, small-group functioning, a tutor's social congruence, and level of achievement, and how they influence each other (Schmidt & Moust, 1995). The SEM technique visualizes such relationships through correlations between variables that a study is interested in. Path modeling is a type of SEM that provides a graphical representation of the relationships between variables. Compared to other methods, path modeling can be used to answer questions about direct and indirect influences between variables and identify the causal paths that lead from one variable to another, helping to visualize how changes in one variable can lead to changes in other variables (Kapur & Kinzer, 2007; Noordzij & Wijnia, 2020; Sockalingam et al., 2011). The methods presented thus far have focused on quantitative data, but to understand learning in action, we need to also consider qualitative methods for studying learning processes in PBL.

Qualitative Methods for Visual Representations: Capturing Time and Space

Through the lens of sociocultural perspectives, learning is a phenomenon created through social interactions that unfold over time and are mediated by tools. With these in mind, methods like event maps, CORDTRA, and spatial representation can be used to capture learning processes in a multidimensional way and trace how different activities develop and interact with each other. Specifically, event maps help organize the ways that members of PBL co-construct complex knowledge and identify what events have contributed to the meaningful sense-making in PBL settings. When making sense of rich data that is multimodal and multidimensional, CORDTRA diagrams can help organize the coded data chronologically and address questions regarding the interrelationship between discourse, tool usages, and involved artifacts as they take place simultaneously across a PBL activity (Hmelo-Silver et al., 2008). On the other hand, spatial representations present the spatial interactions and physical dynamics of elements involved in PBL, which can be used in parallel with event maps (Bridges, Chen, et al., 2020).

The following section will introduce each visual representation method in more detail including SNA, SEM, CORDTRA, spatial visualization of physical activity, and event maps. In each method, we will illustrate purposes of its use, its features, and how it has been used in PBL settings with some examples. Its affordances and appropriate ways to use the method will be discussed as well.

Social Network Analysis

Social network analysis (SNA) is a method that identifies patterns of social relations or interaction in a social group based on connections between actors, which are the main constituent(s) that a study is interested in, such as individuals, resources, communities, ideas, and so forth depending on research questions (Carolan, 2013; Wasserman & Milton, 1994). Research in PBL and computer-supported collaborative inquiry are often grounded in sociocultural theory, where students' interactions with other people and artifacts in classrooms are key factors. To understand the dynamics, it is essential to identify active and peripheral participants or tasks involved, the direction of the interaction, the level of engagement, and changes in participatory patterns over time (de Laat et al., 2007). SNA provides such relational information by computing the strength of the relational actions, identifying their directions, and visualizing the holistic patterns of interaction between actors and their temporal dynamics. This helps us understand the complex dynamics of the classroom settings. Recent studies have used SNA to present patterns of collaborative knowledge building or problem solving with text-based data derived from digital learning environments such as online discussion boards (Y. Chen et al., 2021; C. Chen & Kuo, 2019), computer-based assessment tools (Li et al., 2022), or Knowledge Forum (B. Chen et al., 2015; Tao & Zhang, 2021; Zhang et al., 2009; Zhang et al., 2011).

Because SNA centers on social interaction, the unit of analysis is not individuals but the interaction between or among actors within a social network (e.g., an exchange of messages between students in a discussion). Thus, the interaction that a study is interested in should be clearly identified. SNA consists of actors and links (i.e., ties). In PBL classrooms, actors could be individuals (e.g., instructors and learners), artifacts (i.e., discussion posts and messages), or online learning behaviors (e.g., clicking, watching videos, content analysis with codes representing knowledge-building behaviors; see B. Chen et al., 2015; Tao & Zhang, 2021; Zhang et al., 2009; Zhang et al., 2011). In SNA, two actors interacting with one another are assumed to be connected by a link. The link can connect two actors either from the identical or different type of actors (e.g., individuals, artifacts, learning behaviors, etc.). Such information can be visualized through SNA tools (e.g., Social Networks Adapting Pedagogical Practice (SNAPP), NetMiner II, Mzinga, and Gephi) in a graph consisting of nodes and lines, which represent actors and links, respectively (de Laat et al., 2007; Ortiz-Arroyo, 2010). For instance, as shown in Figure 1, a study by Y. Chen et al. (2021) displays structure and relations of a group's interaction in a PBL online discussion forum. The nodes indicate students who participated in the discussion activity, and relational arrow lines between the nodes represent the interaction between two students in the group through discussion posting. Moreover, the directions and strengths of the interactions are displayed through the directions of the arrows and the thickness of the lines, which can be also presented through numerical values, respectively. Therefore, it is necessary to precisely align the nodes and lines with operationalized variables involved in a study based on its research questions, which largely influence interpretation of analytical results.

Density and centrality are the two indicators of SNA that are commonly utilized (de Laat et al., 2007; Ortiz-Arroyo, 2010). Density can provide a measure of the overall and specific connections between the nodes (i.e., actors). The

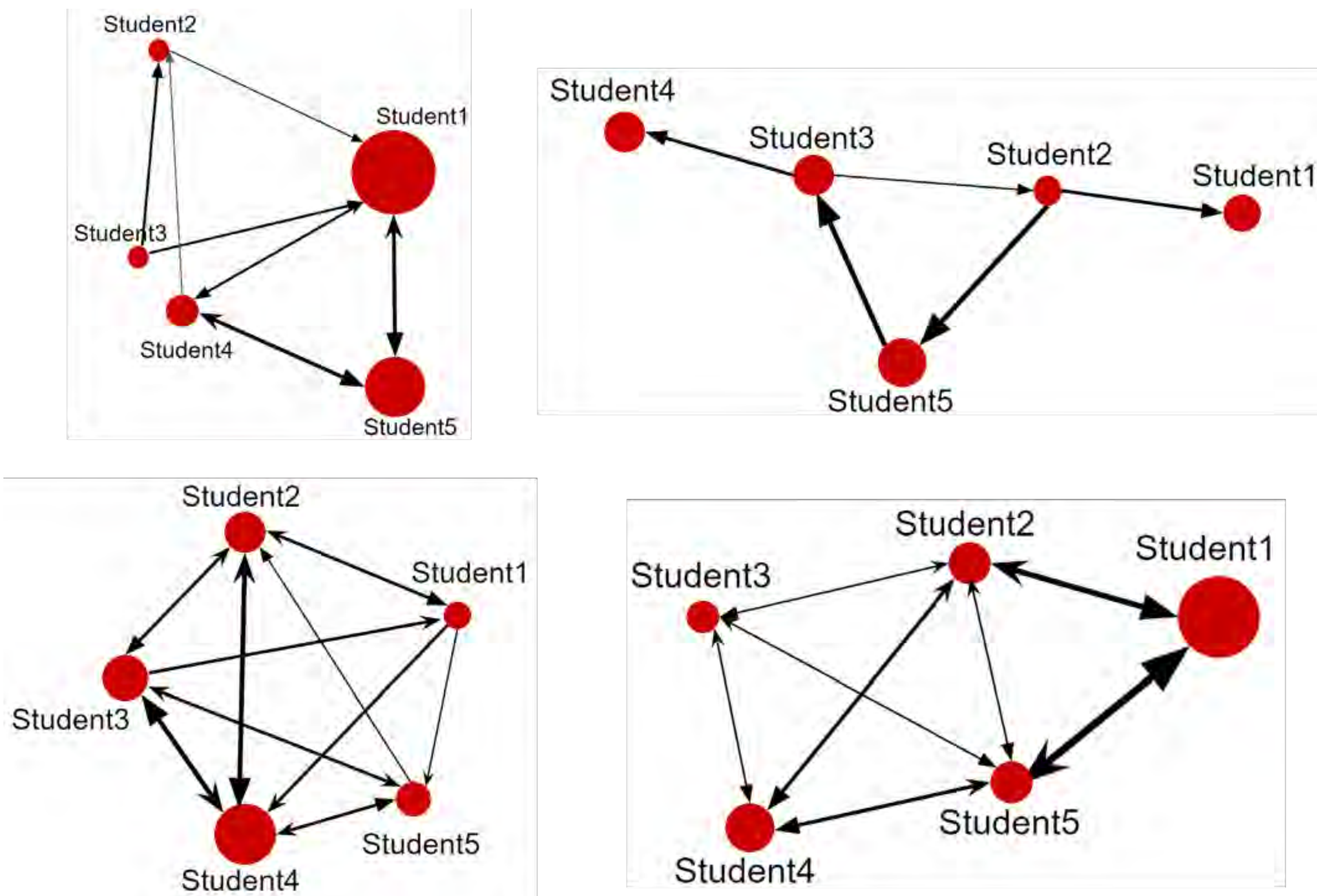

Figure 1. Examples of SNA (Y. Chen et al., 2021)

density of a network is defined as the number of relational lines observed in a network divided by the maximum number of possible links (Scott, 1991). For instance, a group with a teacher's presence exchanged more messages with one another; in other words, more nodes were linked with one another, indicating a higher density value. Additionally, the weight of each line or value ranging from 0 to 1 or 0% to 100% can also represent how strong a relation between nodes is (e.g., the number of comments an actor has provided to a certain actor). A node's relative position within the context of its network describes its centrality. Within a social group, several or a few nodes occupy central positions, others are located in the periphery, and the rest lie somewhere in between. As Figure 1 shows diverse shapes of the networks, the nodes' relative positions decide the structure of the social relations. Specifically, centrality describes the extent to which an individual interacts with other members (Wasserman & Milton, 1994), which measures the level of influence, contribution, exposure, or even participation in the network. In some cases, the size of a node also reflects its centrality in the social network. There are two forms of centrality—in-degree centrality represents the number of inbound lines linked with a certain node (e.g., the number of participants who have responded to a certain member), whereas out-degree centrality indicates the number of outbound lines connected to other nodes (e.g., the number of chats a participant has sent to others; see Li et al., 2022).

To further deduce meaningful findings and enhance validity, SNA has been frequently accompanied by statistics, such as analysis of variance (ANOVA) and the least significant difference (LSD), to articulate whether targeted behaviors are significantly meaningful. For instance, in a knowledge building inquiry environment, Zhang et al. (2009) conducted SNA to examine the effect of different participation structures on the extent to which students read other students' posts and created links among them. They accomplished this by investigating whether the quantified relational data showed significant differences between the different participation structures through ANOVA. Another recent trend of use of SNA is that it has been triangulated with other methods including quantitative and qualitative methods such as pre- and post-assessment analysis, coding and counting, interviews, and content analysis to enhance one's validity or further elaborate what has been found through SNA (C. Chen & Kuo, 2019; B. Chen et al., 2015; Li et al., 2022; Tao & Zhang, 2021; Zhang et al., 2009; Zhang et al., 2011). SNA has been widely used and has established its own position as a visual representation method in PBL and collaborative inquiry research. It is a useful tool for identifying patterns of social relations or interaction in a community by looking at connections between actors, their direction and strength, and changes in the relationships over time.

Structural Equation Modeling and Path Analysis

Structural equation modeling (SEM) is a very general yet powerful statistical modeling technique that refers to the structural relationships between theoretical constructs that are also viewed as latent factors (Lei & Wu, 2007). Latent factors such as problem-solving skills in math can be described as abstract variables that are unobservable and denote the representation of a certain concept in a model (Bollen & Hoyle, 2012). Thus, researchers should define latent variables through observed variables that represent them. Specifically, SEM is used to test hypotheses concerning the connections between the observed and the latent variables. SEM also operates as a confirmatory method, focusing on hypothesis testing in the analysis of theories relating to specific phenomena (Teo et al., 2013). The increased application of SEM across different disciplines can be attributed to the multiple computer programs (e.g., LISREL, AMOS, Mplus, Mx) that increased accessibility to researchers who find this method appropriate for answering research questions. A few examples of the different types of research questions that can be answered using SEM include questions that might involve assessing the relationships between variables like technology usage, teaching practices, and student performance to assess the effectiveness of technology integration in educational settings, or research exploring the relationships between variables such as school climate (e.g., safety, supportive environment), student well-being, and subsequent academic success. Research in the educational field has benefited from SEM's generalizability and flexibility with respect to testing different hypothesized or proposed relationships between variables across various learning environments (Kieffer, 2011; Teo & Khine, 2009; Wang & Holcombe, 2010). Path analysis is a special case of SEM that can help examine the relationships between different variables and compare the strength of the effect these variables have on the outcome. It requires the researcher to explicitly define how each variable relates to the other and allows researchers to break apart the various factors that directly or indirectly impact the outcome. The relationships are described through path analytical diagrams consisting of arrows from variables drawn to other variables to indicate theoretically based causal relationships. A single-headed arrow points from cause to effect. A double-headed, curved arrow indicates that variables are merely correlated; no causal relations are assumed (Stage et al., 2004), as shown in Figure 2. The magnitude of the strength of the relationship between two variables is defined by taking the product of the path coefficients along the pathway of the two causally related variables. The numerical values by the arrows in Figure 2 are path coefficients showing the direct effect of an independent variable on a dependent variable in the path model.

Students' approach to learning in a PBL environment is a complex phenomenon and influenced by multiple factors. The relationships between these factors and how they impact student learning might not be easily understood. In this section, we delve into how path analysis has been used to visualize these relationships between the various components in PBL learning environments across a few studies. In contrast with the other examples shown, these have tended to be grounded in cognitive theory. Noordzij and Wijnia (2020) used path analysis specifically to investigate the relationship between the latent constructs of student achievement goals, problem quality-related characteristics, and autonomous motivation. Significant positive path coefficients established a direct impact of a few variables like problem familiarity and critical reasoning on the latent construct of autonomous motivation. A negative path coefficient between collaborative learning to autonomous motivation defined a negative relationship between the two variables. An example of a study grounded in sociocultural theories used path models to study the relationships between the problem rating

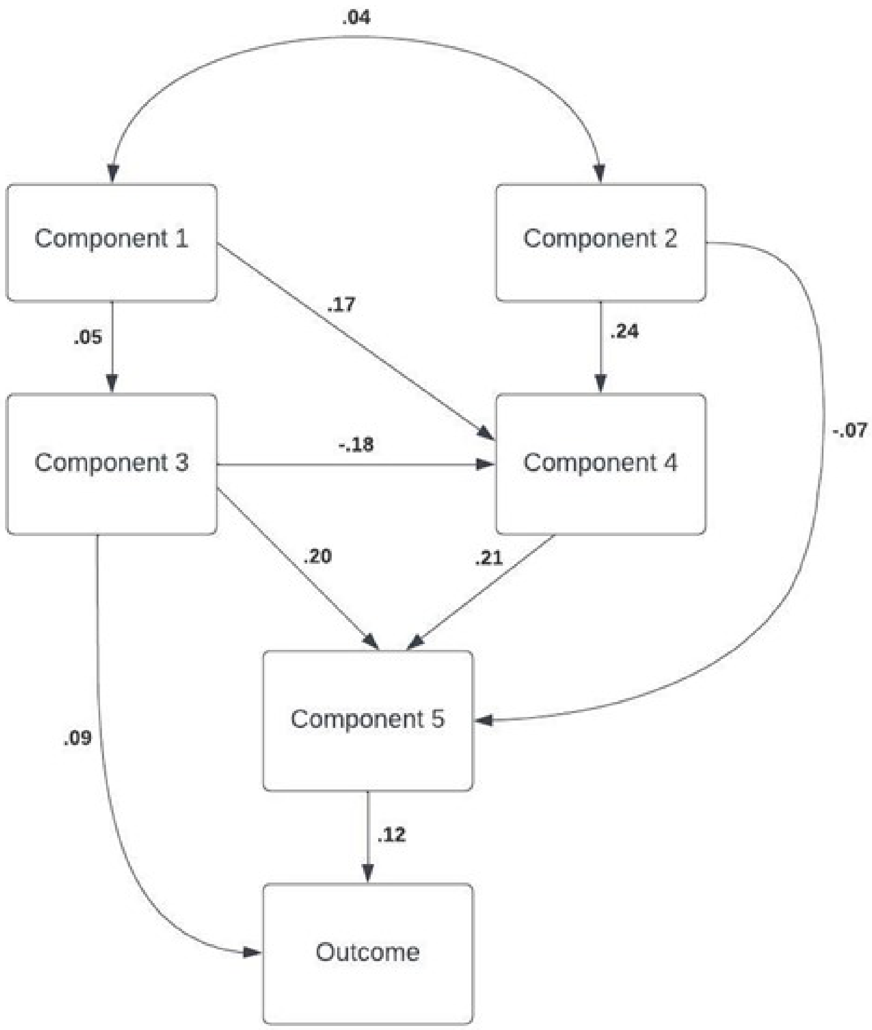

Figure 2. Example of Path Analysis

scale items, achievement-related classroom behaviors, and academic achievement (Sockalingam et al., 2011). The path coefficients were again used to interpret the results of this causal model. Schmidt & Moust's (1995) investigation used path analysis to envision the associations between the different components in a PBL environment with a focus on the importance of the nature of the problem and its impact on student learning and achievement, other motivational processes in PBL and how it might affect a student's intrinsic motivation, and the role of a tutor in contributing to student learning. The quality of a problem is critical to student learning and is not just determined by the content of the problem but by how it supports motivation, engagement, and, hence, student achievement. However, considering the characteristics of the problems are theory-based, their impact is not easily observable. Path analysis is a useful analysis tool when it comes to decomposing the relationships between variables that are not directly observable and testing a theoretical model. Both studies utilize path analysis to test hypothesized models of causal relationships between problem characteristics and student motivation and achievement. Path analysis helps visualize the multiple paths (direct and indirect) in which these relationships exist, and the path coefficients explain the magnitude of the impact of these problem characteristics. There have been other studies that have used path analysis to explore the direct and mediated effects of the educational context on learning approaches in PBL classrooms (Araz & Sungur, 2009; Gustin et.al, 2018; Schmidt & Moust, 1995). The studies concentrated on investigating elements such as prior knowledge, the learner's belief system, intrinsic goal orientation, and other factors that are not readily apparent but might have an influence on a student's learning. A path diagram made these abstract components visible, simplifying the process of analysis and interpretation.

CORDTRA

CORDTRA (generalized from Luckin et al.'s 1998 CORDFU approach) is a timeline representation allowing researchers to superimpose multiple coding schemes, gestures, computer trace data, and participation data to identify dynamic relationships among different aspects of learning environments. Specifically, it helps researchers understand how aspects of discourse are related to each other over time and to the tools being used in the collaborative learning process, which requires them to consider longer trajectories of activity (Mercer, 2008; Reimann, 2007). CORDTRA can foster a holistic visualization of data while integrating across multimodal data sources to understand an activity system (e.g., discourse, gestural, or tool-related codes as shown in Figure 3).

CORDTRA diagrams are constructed by creating a unified transcript that integrates the log file data of all the tool hits with the coded discourse data. These discourse data are recorded as the number of turns, as shown in Figure 3. Initially, these diagrams were graphed in spreadsheets; however, there has since been R code developed to create these (Chen, 2013). Studying the CORDTRA diagrams often suggests points in the discourse needing further investigation.

CORDTRA diagrams were first used to examine face-to-face collaboration in PBL to investigate how constructing a drawing mediated learning (Hmelo-Silver, 2003). This research used a multidimensional coding scheme to capture group discussion along with drawing activity and gestures. These analyses illuminated how the tutorial unfolded and how an external representation mediated collaborative learning. For example, the CORDTRA diagram highlighted that medical students engaged in causal reasoning while were constructing a representation as they made connections between patient signs and symptoms and underlying explanatory mechanisms (Hmelo-Silver, 2003).

In technology-mediated environments, CORDTRA can be particularly powerful in understanding how technology tools mediate learning. For example, in a study with the STELLAR PBL environment, we used CORDTRA diagrams as part of contrasting case analyses of more and less effective groups in a PBL educational psychology course (Hmelo-Silver et al., 2008). Students engaged in three online PBL activities, in which they redesigned a lesson presented in a video case. The following example focuses on collaboration during the second problem. This problem required that students use several online resources while viewing two contrasting video cases. We coded the discourse for features related to cognitive engagement and examined the records of all tools accessed and entries made by the students and facilitators in personal notebooks, threaded discussion, and a group whiteboard. This afforded the opportunity to investigate the discursive contexts where tools were used.

In the CORDTRA diagrams shown in Figures 4 and 5, the data are arranged in chronological order on the horizontal axis. At the bottom of each diagram, there is a running count of lines of codes. Since we are choosing to analyze only certain steps of the activity for each group, the line counts begin at different numbers for each group because Group 2 engaged more with the STELLAR tools in earlier activity phases than Group 1.

The vertical axis shows the categories of tool usage, discourse codes, and speakers. The horizontal axis shows the number of tool-related events, either a log entry or a discourse turn. The bottom seven categories represent tool

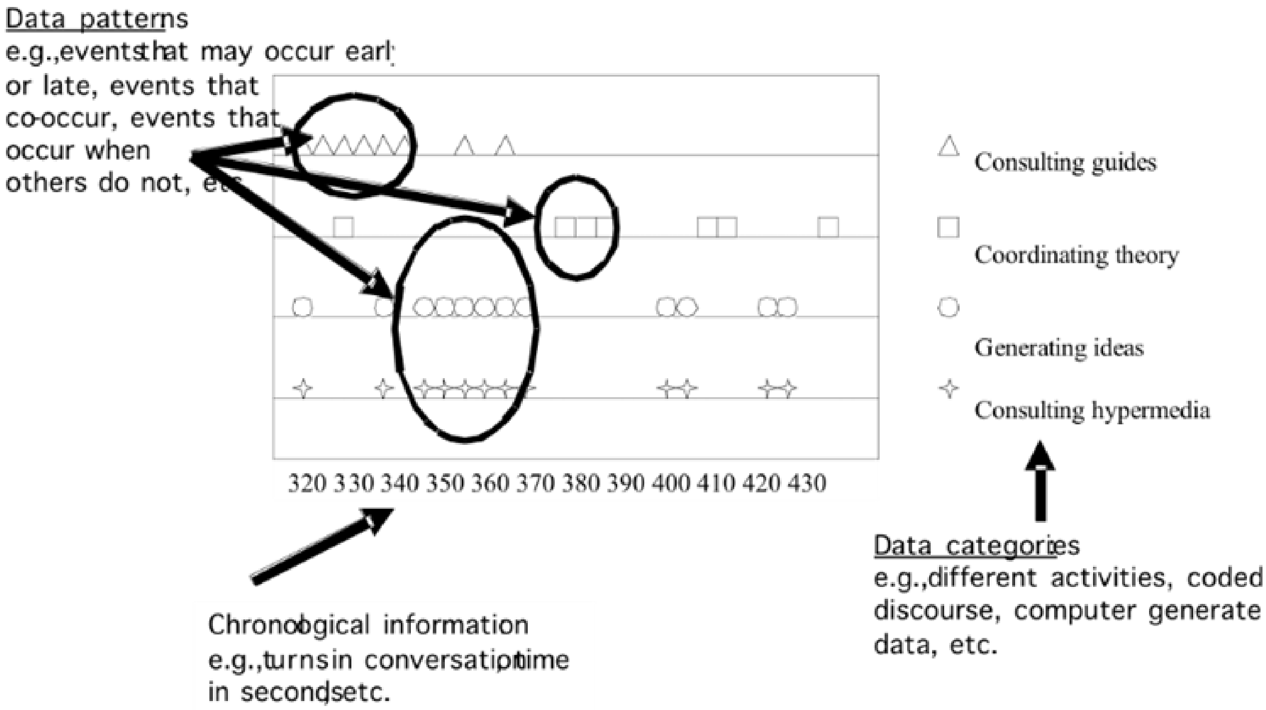

Figure 3. CORDTRA Diagram (Hmelo-Silver et al., 2008)

usage (i.e., log data) by any member of the group. The top six or seven categories represent speakers. The remaining categories represent discourse codes.

In particular, the CORDTRA diagrams were used as part of a contrasting case study to examine facilitator moves, the relation between different kinds of discourse moves with each other and with technology, and student collaboration. One distinction between the two groups is how the groups involved the course facilitators. In Group 1, facilitators were involved early and often and asked most of the explanatory and metacognitive questions. Two students dominated the discourse, though other students contributed. The facilitators joined Group 2 much later and made few questioning contributions. In this second group, the students asked questions throughout the problem duration. The group participated evenly except for one student who joined late in the group's effort. He built on another student's ideas, based on personal experience.

Another aspect of how CORDTRA diagrams help in distinguishing collaborative activity across the groups is by showing the general relationships between discourse and tool usage. In Group 1, the students initially viewed the video and the hypermedia, but after line 650, none of the group members used these two resources until the end of the collaborative phase at line 1000. The content of their online postings was intermixed with conceptual, social, task and tool-related talk throughout their work on the problem. There was some discourse about tools as a problem midway in the discussion. In contrast, Group 2 engaged in minimal social and tool related talk—they largely discussed conceptual ideas with a small amount of task talk sprinkled throughout. Group 2 returned to the STELLAR resources (video case, hypermedia) at intervals throughout the discussion (e.g., lines 850–925, 1050–1100, 1275). Resource usage was often in response to explanation questions as Figure 5 shows (e.g., line 1050), suggesting that Group 2 was using the resources to answer their questions. This diagram was also used to visualize group participation, collaborative activity, how that was affected by facilitator interventions, and ways in which students built on each other's ideas.

Micro-ethnographic analytical approaches attempt to trace the intersubjective and intercontextual nature of situative learning (Greens & Bridges, 2018). These approaches in PBL learning environments help explore the discourse-in-use amongst students while they collaborate and negotiate with each other to construct solutions to ill-structured problems, through and in micro-moments. Drawing on video recordings assists in identifying rich points, which are a central

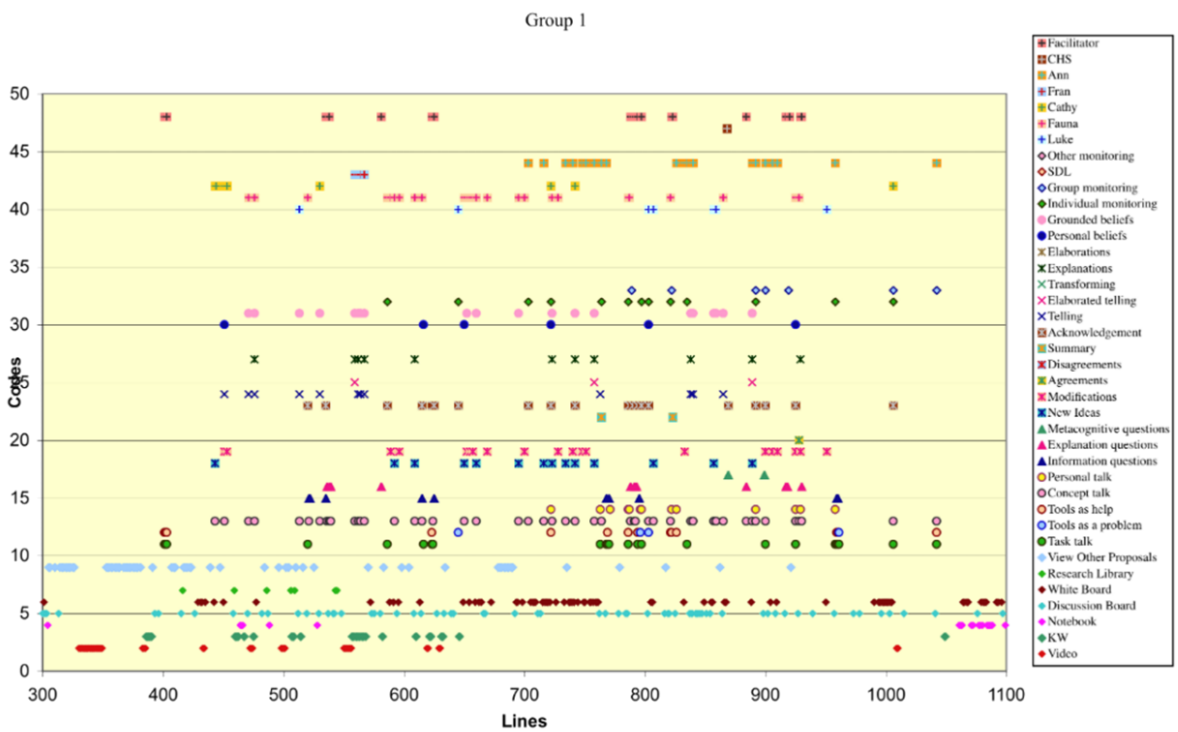

Figure 4. CORDTRA Group 1 (Hmelo-Silver et al., 2008)

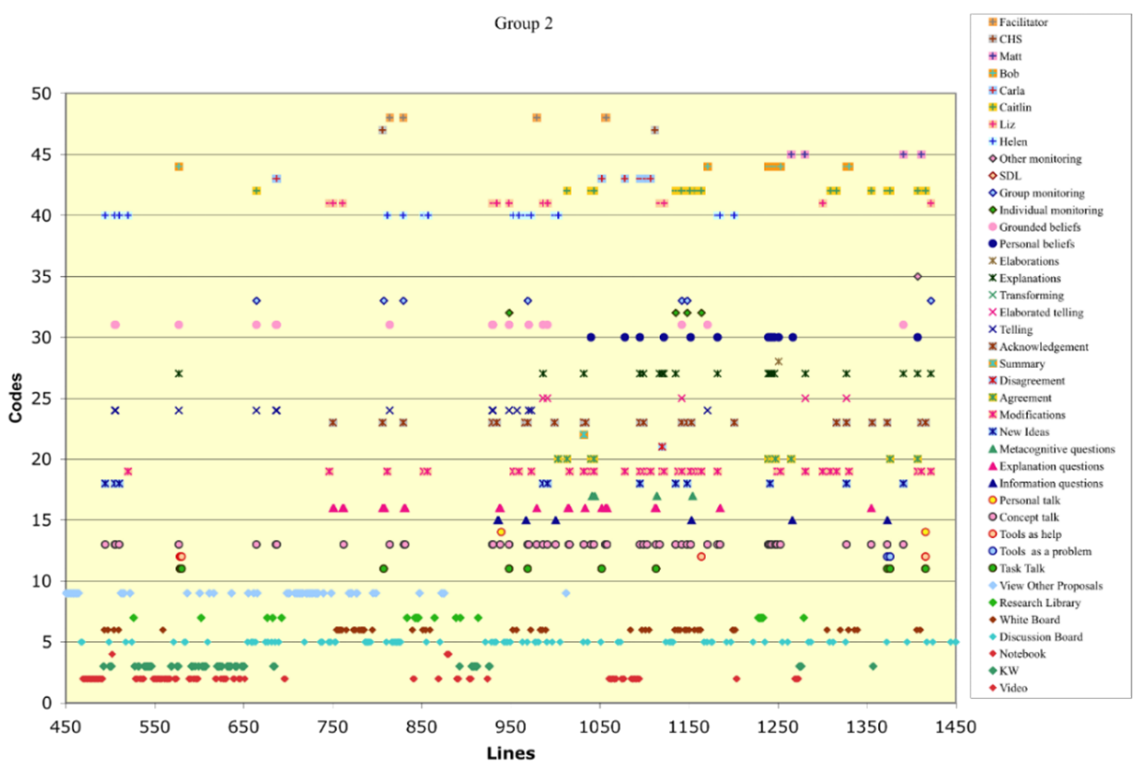

Figure 5. CORDTRA Group 2 (Hmelo-Silver et al., 2008)

point of analysis and provide a basis for a logic of interpretation (Agar, 2006). Despite identifying these moments, interactions between the participants and the other components in a complex PBL learning environment, which is also defined as the “living environment” by Gruppen et al. (2019), are not easily observable.

Event Map

Like other visualization tools that build on a sociocultural perspective, event maps are used to apprehend learning as a socially-constructed process. To capture holistic pictures of the learning process, especially in PBL and CSCL classrooms, we need to understand what disciplinary concepts students have developed and how students have constructed the meanings in and through complex and ill-structured social contexts (Green & Bridges, 2018). To do that, one discourse-based ethnographic approach, interactional ethnography (IE), has attempted to trace epistemological processes in complex learning contexts by reconstructing participants’ interactions (e.g., dialogues with peers and a teacher, engagement with technologies, multimodal materials, artifacts, etc.) with a graphic representation called an event map (Bridges, Hmelo-Silver, et al., 2020; Green & Bridges, 2018). The event map (Figure 6) is a visual representation method to show the chronological relationship between learning resources (e.g., texts) and participant’s interaction (e.g., learning dialogues), which helps determine how participant’s changes in knowledge through the resources in one context lead to consequential learning across other contexts (Bridges, Hmelo-Silver, et al., 2020). In other words, the map affords a place to identify socially and academically consequential discourse moments that are tied to different learning resources, and to make connections across other contexts. As such, it assists in making theoretical inferences regarding interplay between epistemological processes with learning resources and how engagement in learning contributes to construction of meanings.

Event maps have a flexible format and can be adjusted to one’s dataset and research context. In this section, we focus on one of the event maps presented by Bridges, Hmelo-Silver, and colleagues (2020) as an exemplar from a medical school PBL context. The authors generated the event map based on video data and artifacts used or created during the process of learning. The map includes chains of activity identified as consequential events to learning, different sites and times for learning, the evolution of artifacts, and participants’ interaction during the key learning moments with the resources in collaborative spaces. As shown in Figure 6, first, a person needs to select several related key classes or activities that lead to meaning making. Then, the person should provide overall contextual information of the key events including a specific year, semester, a date of each case selected, a topic of the class, learning activities, and so forth in order to show how the cases are linked to macro-level of social contexts. Moreover, based on video data, a series of consequential events for each class in a chronological order, participants, and timestamps for each event should be placed on the map. To make connections between learners’ interaction, use of the materials, and learning activities, the mapping person should provide a brief description of each learning activity, key social events, and related learning materials (e.g., artifacts, multimodal texts, etc.). Furthermore, a transcript of participants’ discourse should be mapped onto the events located on the map, which allows to visualize how chains of social practices are connected to disciplinary processes. As a result, that is likely to lead readers to recognize engagement patterns of meaning making in complex learning environments.

With this visual representation method, Bridges, Hmelo-Silver, et al. (2020) examined how a group of medical students and their facilitator collectively engaged with learning materials to construct a conceptual understanding of cardiovascular physiology in their PBL tutorial group. Specifically, the event map in the study presented how the students accessed, reviewed, appropriated, and devised multimodal digital and visual texts related to the topic in response to interaction with their facilitators within and across one PBL inquiry cycle. To do that, they anchored three key tutorial sessions that were intertextually relevant and consequential to their meaning-making. Moreover, they placed contextual and learning information (e.g., time, sites, learning objectives, learning materials they used, and content of learning activities) across social levels (i.e., an individual, group, and classroom-level) to show how individual- or group-level practices in the conceptual learning with learning resources are interrelated to another. To be specific, on October 19th (Figure 6), they exhibited PBL inquiry events (e.g., generating alternative hypotheses, identifying knowledge gaps, and identifying learning issues/objectives) and their brief descriptions. Additionally, what and how tools relevant to the event were used are illustrated. They also added relevant transcript excerpts of the student’s discourse or facilitator’s support. For instance, in Tutorial 1 at 1:44:45, they explicitly showed that participants engaged with P waves characteristic of right and left atrium enlargement in Case 1 sequential discourse as part of the problem scenario activity with Artefact 5, P wave morphology. Consequently, they could reconstruct the key phases of the PBL inquiry process and trace how use of the digital and multimodal texts across social contexts became consequential for building a conceptual understanding of the topic.

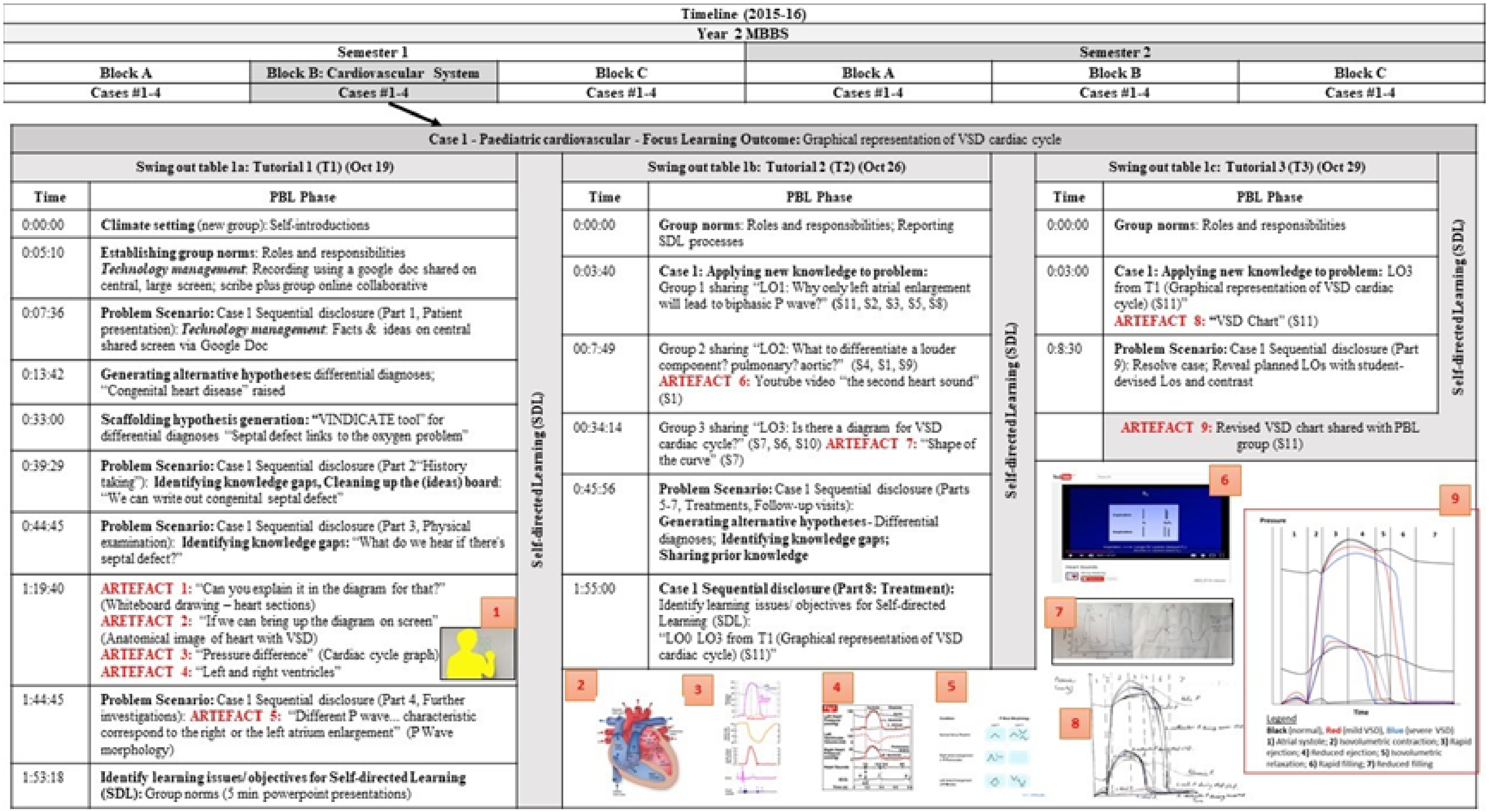

Figure 6. An Example of Event Map (see Bridges, Hmelo-Silver, et al., 2020)

Along with the event map, another visual representation method, spatial representation, can be used during the micro-analyses in IE to closely look at and trace moment-by-moment and over time discourse in relationship to learning resources.

Spatial Representations of Physical Activity

A few studies have explored mapping spatial and interactional participants' discourse to better understand their interactions with each other and the other entities in the learning environment. Spatial representations help in visualizing how the learners use the physical space to work with other learners and the resources while they are engaged in the learning process. In a PBL classroom, where students work individually or in small groups and use a whiteboard or similar artifacts to co-construct knowledge, understanding the affordances of the physical space through a visual representation paints a more vivid picture of the learning environment and process. A few of these representations, which will be discussed in detail later in this section, include converting colored images into black and white outlined images and providing layouts of the classroom configurations while mapping learners playing different roles and the teachers to these configurations. These visualizations are often charted against participant discourse to provide the readers with a complete picture of how these interactions unfold over time.

A micro-ethnographic study by Bridges, Chen, et al. (2020) was designed to explore the complexities of group learning processes in an inter-professional healthcare program. The authors conducted a contrastive video analysis to compare moment-by-moment synchronous spatial and physical configurations and associated discourse and online activity to read into participant interactions. The evolving physical configurations revealed that while one group was, spatially, more evenly grouped and physically oriented to a group leader, despite distributed leadership, the other broke into subgroups at a public forum event that had caused spatial disruptions. The graphic representations of changing physical configurations, with the groups anchored to the discourse and the participant actions, helped the researchers study the cohesiveness of group interactions. This was done using nodes, blank and shaded, that represented an empty or occupied seat and arrowheads of multiple shades that indicated the direction of interaction and the direction of gaze towards another individual or device. The letters, in different formats (i.e., underlined, italicized, or struck through), indicated the participants' posture (i.e., looking at their device, leaning forward, or sitting back). The synchronous changes in physical configurations through these representations helped the authors interpret the interactions within the group to better understand the group dynamics.

Another example of spatial representation in the form of black and white images was used to examine collaboration in a group of medical undergraduate students and their facilitator in a PBL context in an interactional ethnographic study by Bridges, Hmelo-Silver, et al. (2020). In this study, with the event map and the spatial representation of physical activity, the different levels of micro-analysis were centered around the development of intervisual ties and actions, focusing on specific interactional moves in each phase of the PBL cycle across three iterations. The black and white images generated from video clips helped contour the participants while preserving their identity and yet drew attention to their gestures and movements as shown in Figure 7. These images mapped against each step of the representation of the chronological relationship between texts and talk, as represented in the event map described in the previous section (Figure 6), made students' interactions with each other and the various artifacts. They highlighted the embodied actions of the participants, leading to a better understanding of the interaction among talk (discourse), gesture, visual and aural information, and kinesthetic and proxemic orientations. Thus, taken together with an event map, the spatial representation of physical activity can inform how students' interactions with peers and artifacts have shaped their problem-solving processes. Figure 7 provides one such de-identified frame where a student was asked by a peer to draw a figure on the whiteboard. Here the student is standing in front of the whiteboard as a response to the peer's request. The mapping and micro-analyses in the study illustrated how both the social and the cognitive dimensions of learning can be traced as intertwined chains of action, discourse, and multimodal texts. However, the authors in the article do not provide any explicit description regarding how this mapping took place, thus this could be an area for future researchers to consider.

Spatial representation helps spotlight the differences in the physical dynamics mapped out temporally. Exploring the compositions of spatial representations plays an important role in drawing inferences. Thus, these representations can assist researchers in analyzing interactions between the participants and different components in PBL contexts, where understanding how the verbal discourse among the learners unfolds while they collectively build their knowledge.

Potential Pitfalls of Visualizations

In the previous sections, we introduced several visual representational methods that PBL researchers can use to display data from complex and dynamic learning contexts such as

Figure 7. Spatial Representation of Physical Activity (Bridges, Hmelo-Silver, et al., 2020)

PBL classrooms. Although they afford new ways to organize, analyze, and display data, which could lead to new insights to researchers and readers, these visual representations can pose some challenges. The following are the three potential pitfalls to consider with visual representation methods.

First, the visual representation methods might add an extra layer of complexity in analyzing and interpreting data. As mentioned above, sociocultural approaches to PBL attempt to capture and explain holistic and systemic learning processes and their environments. In other words, there are various datasets to analyze and integrate into the results and numerous components and information to deliver. However, visual representation methods may not always be easily interpreted, especially for those who are not familiar with the tools and educational theories, and may add another layer of complexity with the multiple modalities used (Avgerinou, 2007; Knox, 2007; Machin & Van Leeuwen, 2007), leading to a high cognitive processing load (Eppler & Burkhard, 2007; Eppler et al., 2006; Tufte, 1997; Ware, 2019). Even from researchers' perspectives, these visualizations may be quite time consuming to construct. As such, it is suggested to ask questions such as whether visual representations convey information in a more complex manner than necessary, whether they contain redundant or unnecessary content that could distract one's understanding, and whether the format used to represent information/knowledge is universally understandable (Bresciani & Eppler, 2015).

Moreover, one of the practical implications of using these representations to communicate information is the prior knowledge designers and users need, especially for SEM and SNA visualization methods. The types of prior knowledge required include an understanding of the content being represented and the components of the visualizations (SNA, SEM, path analysis, etc.) for data representation and interpretation, and working knowledge of the statistical tools used to design them (Van Wijk, 2006). For the qualitative methods (e.g., CORDTRA, event maps), researchers need to understand the assumptions and methods used to generate the visual representation and realize the need to help the reader interpret these complex visual tools and how they support particular interpretations. Visual representations provide a powerful medium for finding causality, forming hypotheses, and assessing available evidence (C. Chen, 2005). However, limited knowledge of the visualization method can prove to be a major limiting factor. This can be addressed by extensive training and support for designers, but there is still a risk of reducing the audience who can read these visualizations and interpret them in the appropriate manner. It is also important for researchers to understand that visualizations do not stand alone: When presenting visualizations, authors need to help direct readers attention to key aspects of the visualization as well as provide adequate context to support interpretation. It is also important to be parsimonious to support interpretability. For example, in early uses of CORDTRA representations, we tried to fit over 100 variables in a diagram, and it did not support identifying patterns. In contrast, using fewer variables (generally less than about 25), we could see patterns and identify changes in collaboration patterns when it would be useful to zoom in and do finer grained analysis (e.g., Chernobilsky et al., 2003; Hmelo-Silver, 2004).

Lastly, visualization tools, when used properly, can effectively communicate complex ideas and illustrate the dynamic process of PBL. However, if an inappropriate visualization method is chosen, it can result in misinterpretation or misrepresentation of the data (Eppler & Burkhard, 2007; Nicolini, 2007). As Glenberg and Langston (1992) demonstrated in their study, an inaccurate visualization is worse than the absence of it. Moreover, researchers who present their data through visualization techniques may unconsciously highlight or zoom in on certain aspects of the data while disregarding other important details. By omitting crucial components to the data corpus, certain visual representations may distort the information they convey (Nicolini, 2007). For example, one common misconception regarding SEM is that a good fit indicates a strong impact on the dependent variable (Kroehne & Steyer, 2003). Moreover, while SEM can examine causal links among variables, it cannot definitively establish causality. Additionally, selecting certain variables to investigate may result in overlooking other factors that are equally critical to the dependent variable (Kroehne & Steyer, 2003). This can cause readers to overlook critical information or oversimplify the complexity of PBL.

Conclusion

The current paper introduces diverse visual representation methods that have been widely used in PBL (and computer-supported collaborative inquiry more broadly) including SNA, SEM, CORDTRA, event maps, and spatial representations of physical activity, provides insights into the use of the specific visual representations, and discusses potential pitfalls for the better use of visual representation methods. In quantitative studies, which usually deal with relatively large amounts of data, SNA, SEM and path analysis have been widely used to identify interaction patterns among students, teachers, and tools and to see how the patterns change over time. CORDTRA, event maps, and the spatial representations have been utilized mostly in qualitative research studies to represent how learners develop understanding through multidimensional interactions with each other and with the tools in PBL classrooms. Many of these representations focus on collaborative activity in PBL, though others such as SEM may also focus on individual knowledge and beliefs. Although such visual representation methods enable us to visualize and trace complex dynamics and communicate findings with readers, there are also some potential pitfalls, which could mislead the interpretation and communication.

As Larkin and Simon (1987) reiterated, a diagram can (sometimes) be worth 10,000 words. We can often represent ideas and data visually in ways that would be really hard to make sense of otherwise. In particular, PBL is a complex and multidimensional environment. Visualizations help make salient elements of the dynamic interactions in the environment that might otherwise be hidden. They can help us integrate information from different multimodal data sources, provide pointers for where else to delve more deeply into the data, and direct the analyst towards interesting moments and patterns in the data record. However, like any analytic tool, visualizations do not stand alone. We need to understand how to interpret the elements of the visualizations as well as the visualizations themselves. In addition, these visualizations do not construct themselves. Using visual techniques requires expertise in visual analysis techniques, access to appropriate tools, data to be formatted for those tools, and visual literacy for both producers and consumers. All the data visualizations presented here were done after (and often long after) the data was collected. Some of these, such as CORDTRA, event maps, and spatial representations, required substantial time and effort to construct, and while there have been simplifications (e.g., Chen, 2013), the delay in creating these visualizations limits their usefulness for rapid formative evaluation of PBL designs. Tools that enable easy and near real-time generation of visualizations will increase the utility of these tools for research and design, and perhaps prove to be useful tools for teachers. Future developments should provide this automation and flexibility to allow researchers to focus on the interpretations rather than spending their time on complex mechanics. Having tools that can switch between different representations allows shifting perspectives in interpreting data. It is important that PBL researchers are trained in using visualizations to allow sophisticated inferences about the complex learning environments that are PBL.

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