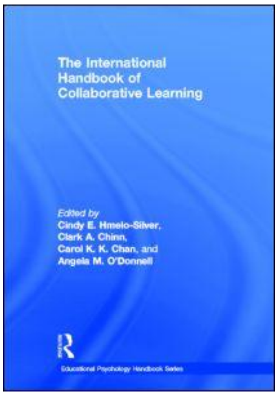

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VERBAL DATA ANALYSIS FOR UNDERSTANDING INTERACTIONS

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WHAT IS VERBAL DATA ANALYSIS?

Background

From the beginning of scientific investigation of the mind, researchers have used verbal data. When the first psychological laboratory was established in Germany, introspection was the dominant research method. In introspection, researchers asked participants to report their conscious experiences during exposure to various sensory stimuli, such as colors or tones. The researchers believed that introspection could reveal the elements of basic consciousness, which could then be combined to describe all human experiences. It soon became clear, however, that the verbal data produced by introspection was too subjective and unreliable, which led to its abandonment as a scientific method. Psychologists started using verbal data again with the cognitive revolution. The prevailing data collected for psychological research, especially in human memory studies, were response time and error data. However, as researchers began to examine more complex processes such as problem solving, they needed a method that could provide more direct access to the contents and processes of problem solving and reasoning. Newell and Simon (1972) established the use of "think-aloud" protocol, in which participants speak their thoughts while engaging in various problem-solving tasks. This process differed from the earlier introspection method in that it did not force participants to reflect and comment on their thinking. Still, questions were raised about the method's validity, since verbalization can influence the very cognitive process that it aims to investigate (Nisbett & Wilson, 1977; Schooler & Engstler-Schooler, 1990). Distinctions were made between concurrent and retrospective verbalizations. It was argued that while retrospective verbalization influences cognitive performance, the concurrent verbalization of the think-aloud method does not, since it only gives voice to already-ongoing inner speech (Ericsson & Simon, 1993). As the field began studying complex forms of knowledge development, researchers were again in need of a method that allows the examination of complex representational changes accompanying learning and development. Verbal data analysis, often abbreviated to "verbal analysis," was initially developed in the process of meeting these challenges (Chi, 1997, 2006). As the field expands its research focus to collaborative interactions, verbal analysis is being used widely to address research questions that arise in the studies of collaborative learning. This chapter will examine verbal analysis and its use in addressing various questions about human learning and cognition.

Key Features and Underlying Assumptions

According to Chi (1997), "verbal analysis is a methodology for quantifying the subjective or qualitative coding of contents of verbal utterances. In verbal analysis, one tabulates, counts, and draws relations between the occurrences of different kinds of utterances to reduce the subjectiveness of qualitative coding" (p. 273). Verbal analysis is predicated on the belief that verbal data can be treated as a form of objective data to examine the state of participants' knowledge and thought processes. Verbal analysis tries to remove the subjective and qualitative nature of the raw verbal data so that it can produce objective results verifiable by other analysts. To achieve this goal, verbal analysis emphasizes operational definitions and systematic applications of coding that can lead to quantifiable outcomes. Statistics are used to ensure that the obtained results are generalizable beyond the specific sample.

Verbal analysis developed in the cognitive tradition. Its analysis strategies are closely related to the development and application of cognitive theories about problem solving, cognitive development, and expertise. In this respect, it would be fair to say that the method is closely aligned to research questions aimed at understanding human cognition. Note, however, that cognition is no longer equated with individual cognition. Theories of cognition may have started out explaining individual cognition, but this is no longer the case. A comprehensive understanding of how cognition works requires not only an understanding of how individuals perceive, remember, and solve problems, but also how they interact with their social and physical environments and participate in the collective processes of problem solving and knowledge building (Galantucci & Sebanz, 2009; Hutchins, 1995; Resnick, Levine, & Teasley, 1991; Scardamalia & Bereiter, 2006; Stahl, 2006). Although verbal analysis has proven useful in addressing research questions that arise in the studies of individual and collaborative learning, this does not preclude the application of the method to noncognitive questions. Verbal data reveal not only one's cognitive processes, but also affective and social processes as well. The method can also be expanded to analyze nonverbal data such as gestures and activities. The essence of the analysis is to systemize and objectify the process of analyzing qualitative data. Whether to analyze verbal or nonverbal data, or to examine cognitive or noncognitive processes is up to the researchers and questions they aim to address.

Relationship to Other Methodologies

There are many ways to analyze verbal data. Analysis methodologies such as protocol analysis, content analysis, conversation analysis, and discourse analysis all analyze some form of verbal data. These methodologies developed in different research traditions with different analytical objectives, but they share some commonalities. This section briefly compares their similarities and differences. The goal of the comparisons, however, is only to highlight key features of the verbal analysis rather than to make definitive comparisons of different methods.

Protocol Analysis. Protocol analysis is both a method of eliciting verbal reports from participants and a method of analysis. Protocol analysis was initially developed to study the cognitive processes involved in problem solving (Ericsson & Simon, 1993; Newell & Simon, 1972). Researchers typically elicit think-aloud protocols from participants by instructing them to verbalize their thoughts concurrently while they solve problems or carry out other tasks. Protocol analysis and verbal analysis share many similarities, but also have some differences. One key difference is that protocol analysis has a strong restriction on how verbal data should be collected. Because certain types of verbalization (e.g., giving explanations or retrospectively thinking about past events) can influence the thought processes, participants are asked to engage in concurrent verbalizations, that is, to merely give expression to their inner thought processes. Verbal analysis, however, does not require that verbal data be collected in such a way. Verbal analysis was developed more to capture representational changes occurring as a result of learning and the development of expertise. In this research, the influences produced by reflective verbalizations, such as self-explanations, do not need to be avoided, but rather welcomed as mechanisms of learning (see Chi, 1997 for more extended discussions about the differences between verbal analysis and protocol analysis). In spite of the differences, protocol and verbal analyses share much in common. Both use verbal data as windows into cognition and are committed to objective and systematic analysis, which is in sharp contrast to other methods that are rooted more in the qualitative analysis traditions (e.g., Sawyer, chapter 7 this volume; Koschmann, chapter 8 this volume).

Content Analysis. The content analysis methodology analyzes the contents of recorded human communication. It analyzes specific characteristics of the messages and is considered a technique for documentary research (Holsti, 1969). Unlike verbal analysis, content analysis typically deals with existing textual data that were generated as byproducts of various communicative activities, such as newspapers, books, and speeches. The two methods also differ in the kind of research questions they address. Verbal analysis focuses on examining cognitive phenomena, whereas content analysis addresses a wider range of topics, such as cultural differences in communication, detection of propaganda, and the communication trends in political discourse. Although content analysis is often included under the general category of qualitative analysis, content analysis can also be quantitative (Neuendorf, 2002). Quantitative content analysis focuses on quantifying textual data by using methods such as counting the frequencies of certain words present within texts or sets of texts (e.g., how many times the word "science" appeared in the 19th century literature). In addition, it analyzes the relationships of such words and concepts, within the texts, the writer(s), the audience, and the culture. Although analysis techniques are different, as in verbal analysis, quantitative content analysis often emphasizes the need for explicit coding categories and rules in order to produce reliable analyses. The boundaries between verbal analysis and quantitative content analysis are becoming less clear-cut, especially in studies of computer-mediated communications (de Wever, Schellens, Valcke, & van Keer, 2006). These online environments produce a large amount of written texts, which researchers then use to answer questions regarding students' learning and knowledge construction processes. The application of quantitative content analysis to these written communications is quite similar to the application of verbal analysis.

Conversation Analysis. Conversation or conversational analysis is the study of speech in interactions. It analyzes conversations produced in naturally occurring settings and attempts to describe its orderliness, structure, and sequential patterns of interaction within various contexts. It examines recurring patterns of interaction, turn-taking and repair mechanisms, and the social organization of conversation (Goodwin & Heritage, 1990; Sacks, Schegloff, & Jefferson, 1974). Although verbal analysis does not discriminate between verbalizations collected in experimental and natural settings, conversation analysis tends to limit data collection to naturally occurring interactions. Conversation analysis considers that verbal data collected in research settings, such as recordings of interview data or conversations in laboratories, are unnatural, because such data are subject to researchers' manipulations and biases. Another major difference is in the analysis itself. In general, conversation analysis is not guided by theories or hypotheses. In analyzing and interpreting the data, it hardly considers the research situations, genders, or ages of the conversation participants. Conversation analysis views such information as a potential source of bias. It is more focused on studying each conversation as it is and seldom carries out quantitative analyses.

Discourse Analysis. Discourse analysis is used to refer to analyses of discourse whose objective is to understand either the linguistic and psycholinguistic properties of discourses (Brown & Yule, 1983) or the processes that are mediated by the discourses (Gee, 2005). What is of relevance and interest to the readers of this book is mostly the latter kind. In this version of discourse analysis, discourse is considered not just as a medium of communication but a tool to support social activities, identities, and affiliations within social groups, institutions, and cultures (Gee, 2005). Discourse analysis is socioculturally sensitive in that it sees individual actions and institutional dimensions as inseparable, and the realm of its analysis extends beyond the text or dialogue itself. It focuses on larger scale events such as the impact of political and educational policy, economic and cultural influences, or group dynamics that are revealed in the discourse, whereas verbal analysis often focuses on small-scale events such as step-by-step changes in learner's mental models and structural features of individual cognition. Unlike verbal analysis, discourse analysis, with its focus on language-in-use, restricts its analysis to spoken and written data generated in the contexts of natural language use, such as conversations, news reports, books, political debates, media's portrayals, and literary works. In addition to differences in analytical aims and the types of verbal data it analyzes, discourse analysis also differs from verbal analysis in the kinds of analysis it performs. Unlike the more-or-less systematic approach to coding in verbal analysis, discourse analysis adopts qualitative approach to analysis. Discourse analysis is meant to be a "thinking device" with which researchers explore different aspects of the discourse under given questions, rather than as a step-by-step set of rules or procedures.

Although distinctions exist, it is not always possible or useful to draw firm boundaries between different analysis methods. Verbal analysis has much in common with protocol analysis. They share similar theoretical commitments and analysis procedures. There is also quite an overlap between verbal analysis and some versions of the content analysis, with their mutual focus on learning-related issues and the use of systematic coding procedures. Perhaps not surprisingly, researchers typically carry out analyses without explicit references to the methodological traditions with which they are aligned. In addition, researchers often use analysis method that is at the boundaries of different traditions or combine different analytical traditions, a trend increasing with the popularity of multimethod or mixed method research (Hmelo-Silver, 2003). The term *verbal analysis* is used loosely in the rest of this chapter, to refer to analyses that examine verbal data in a manner consistent with the verbal analysis method.

VERBAL ANALYSIS IN THE STUDY OF INDIVIDUAL LEARNING

Verbal analysis has become a standard methodology in areas involving complex forms of learning and problem solving. Two areas of research have been particularly fruitful with respect to verbal analysis. One is with identifying steps and strategies involved in learning and problem solving. This typically involves collecting verbal protocols during problem solving, although the analytic focus varies depending on the research objectives. For example, Simon and Simon (1989) analyzed the problem solving steps students took in physics problem solving and found that participants first read the problem, then evoked relevant equations, completed the equations using quantities given in the problem statement, and solved for the unknown. Chi, Bassok, Lewis, Reimann, and Glaser (1989) similarly studied physics problem solving. They analyzed the kinds of verbalization generated while students studied worked-out physics problems and found that the kinds of verbalization mattered. Students profited from the study of examples to the extent that they explained the solutions to themselves, suggesting the importance of self-explanations.

Verbal analysis has also been used to identify and capture the nature and development of complex representations. In a classic study of children's understanding of the Earth, Vosniadou and Brewer (1992) investigated children's intuitive knowledge about the shape of the Earth. In individual interviews, they asked the children to answer a set of questions (e.g., "What is the shape of the Earth?"; "What is above the Earth?") and to draw (e.g., "Make a drawing of the Earth"). The researchers used the children's verbal answers to identify their mental models of the Earth, which showed that children's models of the Earth were not always the culturally accepted spherical model and the process of assimilating the culturally accepted model was not a straightforward process. Chi, de Leeuw, Chiu, and LaVancher (1994) similarly captured students' mental models of the circulatory system. Based on students' drawing, verbalizations, and answers to a set of questions, they constructed a set of mental models about the circulatory system that students constructed in the process of developing their understanding.

Verbal analysis has provided ways to reveal the content and structure of knowledge representations and helped researchers to understand key differences between experts and novices. In a classic study, Chi, Feltovich, and Glaser (1981) asked physics experts and novices to sort a set of physics problems and to discuss everything they knew regarding a set of physics terms (e.g., Newton's Second Law, block on incline). Participants also read problem statements and thought aloud about the approaches they would take to solve these problems. Results from the sorting task showed that physics experts and novices begin their problem representations using different categories. Experts abstracted physics principles from the problems and included potential solution methods in their representations. Novices, on the other hand, based their representation on the problem's literal features.

As can be seen in these studies, verbal analysis helped to reveal structures and processes that could not be easily captured in more traditional methodologies such as reaction time or questionnaire methods and provided a basis to build theories about how complex forms of learning and problem solving might occur. As the focus of the field shifts toward understanding collaborative learning processes, the basics of verbal analysis are extended and adapted to address questions related to collaboration and collective knowledge building. The next section will examine how verbal analysis is applied to understand collaborative interaction.

VERBAL ANALYSIS IN THE STUDY OF COLLABORATIVE INTERACTION

Understanding the Product of Collaborative Interaction

One of the research questions that occupied researchers at the beginning was the outcome of collaboration. Researchers initially investigated the effectiveness of the collaborative learning condition against individual learning condition and later the efficacy of different collaborative conditions with different scripts or task arrangements (Berkowitz & Gibbs, 1983; Coleman, Brown, & Rivikin, 1997; Okada & Simon, 1997; Rummel & Spada, 2005). In these studies, students' performances or learning outcomes were often assessed based on their verbalizations to individually administered tests (e.g., answers to posttest questions or probes) (Azmitia, 1988; Coleman, Brown, & Rivikin, 1997). This means that analysis methods developed and honed in the studies of individual learning can be used without much change. For example, Azevado, Moos, Greene, Winters, and Cromley (2008) compared self-regulated learning conditions where students regulated their own learning and externally regulated learning conditions where students had access to a tutor who facilitated their regulation. They used the learning materials and tests used in Chi et al. (1994) and carried out more or less the same analyses such as mental model analysis to determine the effectiveness of the two conditions.

Analyses become more challenging when researchers examine the outcome of collaboration at the group level. The need to determine the extent of the group's knowledge arises when researchers ask questions such as whether the group or the individual is the more effective unit (Barron, 2000), whether and how the group produces qualitatively different outcomes than the individual (Shirouzu, Miyake, & Masukawa, 2002), and how to characterize and differentiate group outcomes that may result from different collaborative interactions (Rummel & Spada, 2005). To answer these questions, group outcomes need to be compared against either individual outcomes or group outcomes obtained in different group conditions. Such analysis requires that groups be used as a unit of analysis. Treating the group as a unit of analysis has implications beyond using it as a unit of coding and statistical analysis. It means viewing it as an agent that processes information; that is, as an agent that can learn, solve problems, and carry out complex cognitive tasks. Understanding how this group level cognition works requires addressing conceptual as well as methodological challenges. Different conceptualizations of what it means for groups or communities to understand something as a group leads to different strategies and methodologies. The field is still working out different solutions to these questions (Akkerman et al., 2007), but so far roughly three kinds of analytic strategy have been tried to assess and capture group knowledge.

The first strategy is assessing what a group does or produces as a unit (e.g., group answers, group proposals, artifacts produced by the group). Researchers often assess individual knowledge representations based on individuals' answers to posttest questions or performances on various tasks. In a similar manner, group knowledge and understanding can be assessed based on answers or performances the group produces as a whole (Jeong, Chen, & Looi, 2011), and verbal analysis can be used if the group outcome contains verbalizations in some forms. Barron (2000) adopted this strategy when she compared the problem-solving performances of triads and individuals. In her study, children were asked to solve a series of problems and to complete a workbook alone or collaboratively. Barron compared the workbooks groups produced to the workbooks individual students produced in order to determine the effect of collaboration on problem solving performance. Suthers and Hundhausen (2003) compared the effectiveness of three collaborative groups supported by different representations (e.g., text, matrix, or graph) and used collaborative essays as one of the measures to compare the outcomes of different conditions. Methodologically speaking, this strategy of using group answers or artifacts as a basis to gauge groups' collective understanding is again a straightforward process. It does not require any new analytic approaches and is quite useful for comparing the quality and outcomes of different units. One limitation of this strategy, however, is that the group product may not accurately reflect what the group knows. Depending on how the group members pool their individual resources and interact in the process of generating their group solutions, the group product may be biased toward contributions from certain members but not others.

The second strategy is to assess group knowledge or understanding based on aggregate measures of individual outcomes. The method of aggregation can vary a great deal. The simplest method is probably to sum or average individual members' performance, as was often done in social psychology and organizational research. For example, Austin (2003) assessed the amount of knowledge different industry teams possessed by summing up the knowledge scores of its members. More complex aggregation methods have been tried using verbal analysis. In a study to examine the amount of common knowledge constructed during collaborative learning (Jeong & Chi, 2007), we first assessed individual students' understanding before and after collaborative learning. By comparing the answers that each member of the student pairs gave, we then came up with a set of measures such as "unique total knowledge," which reflects group knowledge as a whole, "common knowledge," which refers to what both members know in common, and "unique knowledge," which refers to unshared knowledge that is only known by one person. For example, if Student A knew 20 knowledge pieces and Student B knew 15 knowledge pieces, of which they held 10 in common, then, as a group, they knew 25 knowledge pieces (unique total), of which 10 were in common (common knowledge) and 15 were unique to the individual, that is, possessed by only one member (unique knowledge). Note that these measures focused on specific aspects of group knowledge and did not assess notions such as intersubjectivity. However, this was one of the first attempts to operationalize group level cognition based on relationships in individual knowledge.

The third strategy is to use group discourse. According to sociocultural theorists, discourse activity itself as an understanding since cognition and learning, including conceptual understanding and conceptual growth, are functions that are accomplished by activity systems and communities of practice (Greeno & van de Sande, 2007; Stahl, 2006). Unlike sociocultural perspectives, verbal analysis, coming from cognitive traditions, distinguishes process and product. Discourse or dialogues are typically analyzed to understand interactive processes, not the contents of group understanding. Still, process and product are not independent, and the contents of group understanding can be captured from the discourse. The application of this strategy can be seen in the analysis of common ground in psycholinguistic research. Common ground, a form of joint understanding, is inferred from dialogue moves, such as acknowledgments or continuations of previous contributions (Clark & Schaefer, 1989). Another example is Jeong et al. (2011) which attempted to capture group understanding based on the artifact-mediated discourse. In this study, students collaborated both face-to-face and online using a tool that allowed them to share individual notes. Analyses captured group understanding by identifying the major contributions to the group space and how each contribution arose from the artifact-mediated discourse. In this study, the discourse consisted of both verbal and nonverbal forms as students often interacted by carrying out certain actions in the environments (e.g., posting a note), thereby extending verbal analysis to include nonverbal actions and activities.

Understanding the Processes of Collaborative Interaction

As the facilitative effect of social interaction became evident, researchers' attentions were directed at understanding the critical mechanisms of collaborative interaction that are responsible for learning gains. Collaboration dialogues were examined in detail, at first in comparison to individuals' talking aloud. Analyses were guided by research hypotheses about the key differences between individual and collaborative learning processes in a given learning or problem solving task. For example, Teasley (1995) analyzed the amount and types of talks produced while fourth graders engaged in computer-based scientific reasoning task (i.e., discover the functions of a mystery task) and reported that *talk dyads* produced a greater amount of talk overall and a greater amount of interpretive types of talk than *talk alones*. Okada and Simon (1997) examined the scientific discovery process by individuals and pairs. Using students' verbalizations and talks produced while they performed a laboratory simulation task, they examined various aspects of the discovery process such as amount of time spent, number of hypotheses and alternative hypotheses entertained. Their results showed that pairs were more active than individuals in entertaining hypotheses and considering alternative ideas and justifications. Shirouzu et al. (2002) analyzed verbal and nonverbal actions as students carried out mathematical tasks (e.g., shading parts of the materials such as origami or cardboard paper). Although both individuals and dyads heavily relied on nonmathematical strategies, dyads tended to shift to a mathematical strategy in their second trials. In order to find the potential reasons for such divergence, they analyzed verbal references, solution paths, and role changes and found that frequent changes between the task-doing and monitoring roles enabled pairs to abstract rules as they worked on solving mathematical problems. These studies all relied on the analysis of verbal data collected during problem solving and learning, but what they examined in their analyses varied depending on their hypotheses.

Although the benefits of social interaction are undeniable, unstructured collaboration does not systematically produce learning. Researchers actively searched for the characteristics of critical dialogue moves and interaction events that strongly predict learning outcomes. Researchers were also interested in how collaborative processes were affected by various factors such as technologies or collaboration scripts. These studies required detailed examinations of how collaboration proceeds. Researchers adopted a number of strategies to identify critical collaboration events or moves. One strategy was to carry out detailed analyses of dialogues and then relate them (e.g., asking questions, monitoring, receiving explanations) to learning outcomes (Chi, Siler, Jeong, Yamauchi, & Hausmann, 2001; Webb, 1989). Another related strategy is to compare how groups differ with respect to various interactive moves either by studying different collaboration conditions (e.g., scripted versus unscripted arguments) (Stegmann, Weinberger, & Fischer, 2007) or creating post hoc groups of successful versus less successful groups based on some outcome measures (e.g., learning gains). A vast array of dialogue features was examined in these studies such as the grounding moves in a multimodal collaborative problem-solving environment (Dillenbourg & Traum, 2006), giving and receiving explanations (Webb, 1989), generation of arguments and counterarguments (Chinn, O'Donnell, & Jinks, 2000), and monitoring and regulation of the learning processes (Azevedo et al., 2008).

Partly due to the sociocultural view's influence, numerous research efforts have been directed toward understanding the overall characteristics of discourse itself that span beyond specific statements, turns, or sequences of moves. Due to confluences of theory and method, it is difficult to identify studies using verbal analysis in this area. However, unlike analyses rooted in the qualitative analysis tradition, analyses more closely aligned with verbal analysis attempt to analyze discourse systematically, often relying on explicit coding schemes and quantitative analyses. In addition, although analyses place less emphasis on individuals, individual level moves are still considered in the context of the larger discourse events. Hogan, Nastasi, and Pressley (2000) examined discourse patterns in peer- and teacher-guided discussions occurring in an eighth grade classroom. They transcribed and analyzed interactions within peer- and teacher-guided small-group discussions in a number of ways. For example, they analyzed discourse at both the macro- (conversational turns) and microlevels (statement units ranging from words and phrases to sentences) and differentiated discourse activities directed to the self (e.g., elaborating oneself) from discourse activities directed to others (e.g., elaborating another's idea). Through a detailed examination of how peer- and teacher-guided discourses proceeded, Hogan et al. showed that, in both peer and teacher-guided small-group discussions, the key feature was working with weak or incomplete ideas until they improved, but how this was accomplished differed somewhat depending on the presence or absence of a teacher in the discussion. In another example, van Aalst (2009) attempted to differentiate three modes of discourse—knowledge-sharing, knowledge-construction, and knowledge-creation discourses—within an asynchronous, computer-mediated discourse. He proposed seven discourse dimensions that can differentiate the three modes of discourse and further subdivided the seven dimensions into 33 subordinate codes. By coding individual students' note postings in the online discourse using the framework, he was able to identify critical discourse dimensions for differentiating the three modes of discourse and to determine the kind of discourses specific student groups engaged in.

ISSUES IN USING VERBAL ANALYSIS

This section examines some of the key issues that analysts need to consider in carrying out verbal analysis. Due to space limitations, this section focuses on general research and analytic strategies associated with verbal analysis. For a practical and step-by-step guide to verbal analysis, including issues of coding units and segmentation, please refer to Chi (1997).

Research Questions and Design

The method was developed to answer research questions about cognition. However, the mechanics of the method can be applied to the studies of noncognitive questions as long as the target constructs or processes are reflected in verbal data. Verbal analysis is a tool. It is up to the researchers to decide which questions to use the analysis for. It would be fair to say, however, that verbal analysis has so far shown its greatest strength in examining questions related to individual and collaborative cognition. Its analyses tend to be microgenetic and suited for examining detailed progression of knowledge development and strategy changes. Verbal analysis is especially suited for the studies of collaborative learning because collaborative interaction typically generates a large amount of verbal data, in both spoken (as in face-to-face interactions) and textual forms (as in distributed interactions through e-mail or chats). With its unique ability to analyze these data and emphasis on systematic and quantitative analysis, verbal analysis is suitable for addressing various issues related to collaborative interactions.

Although some aspects of verbal data are readily quantifiable (e.g., word frequency), interpreting verbal data requires qualitative meaning-making processes. Because of this, some researchers, especially those coming from strictly quantitative research traditions, often view verbal analysis as a branch of qualitative analysis and incompatible with experimental studies. However, although verbal analysis may use qualitative data, its analyses are not qualitative. The essence of verbal analysis is to reduce potential subjectivity inherent in meaning-making processes by systematizing the analyses. In addition, unlike conversation or discourse analyses which restrict themselves to naturally generated conversations or discourses, verbal analysis has been, and can be, used in combination with a variety of research designs, including experimental or quasi-experimental design. An example of experimental studies with verbal analysis is Chan (2001), which compared learning in four different experimental conditions. She collected students' answers to questions (e.g., explain how ducks evolved webbed feet) and recorded students' discussions with peers. Verbal data were used as a basis for comparing the four learning conditions. When collecting verbal data in experimental studies, it is a good strategy to keep the experimental design simple since analysis of verbal data can become quite complex. Verbal analysis has also been used successfully with quasi-experimental studies examining conceptual development and differences between experts and novices (Chi & Koeske, 1983; Chi et al., 1981; Vosniadou & Brewer, 1992) and with descriptive studies that collected verbal data in more-or-less naturalistic settings such as classrooms (Hogan et al., 2000).

Collection of Verbal Data

The elicitation of verbal responses is an important issue when verbal data are used to study individual problem solving processes. Because not everyone is accustomed to think aloud when they work alone, researchers often provide practice or prompting in order to ensure that the process of verbalization does not interfere with the ongoing process of problem solving or discovery process being studied (see Ericsson & Simon, 1993; Chi, 1997 for details on these issues). Such issues and concerns are mostly non-existent when verbal data are collected during collaboration. People tend to talk when they interact. No special instructions or trainings are needed in order to get students to talk. Researchers can just record the verbalizations that occur as part of the naturally occurring interactive processes. Still, there are a few issues researchers need to be aware of when collecting data in collaborative settings. First, the act of recording can make students become conscious of what and how they talk and this might make them behave and interact differently. Researchers thus need to ensure that the act of recording does not interfere with their routine interactive behaviors. Second, even though people do talk when they interact, being in a group does not always make them talk or interact. This is especially the case when collaboration is studied in laboratory settings with randomly assigned group membership. The generic instruction to "collaborate" does not always lead to active interaction among these students. In such cases, care needs to be taken so that students feel comfortable with each other and can engage in the kinds of interaction that the researchers want to examine. The same problem can also occur when collaboration is studied in naturalistic settings. The group might be newly formed, there might be some hidden tensions or conflicts that make members reluctant to talk, or they might not have anything to talk about. In addition, even when group members talk, students might talk about off-topic issues or get into squabbles. In such cases, researchers may prompt students to talk, collaborate, or stay on-task, but need to be aware of the possibility that such prompting or suggestion can influence the group process and dynamics. In general, such prompting should be used only when it does not influence the process that the study aims to investigate. If one's research question concerns examining how collaboration ebbs and flows, for example, then researchers must study the collaboration as is. Prompting group members to talk or collaborate would render the data useless.

By tradition, verbal analysis has typically relied on transcripts of spoken verbalizations. Spoken verbalizations, either in the form of think-aloud or verbal interactions, can provide a more detailed picture of what is happening both inside and between individuals. However, not only have written verbal responses been successfully used in various studies (Coleman et al., 1997), but they are also becoming increasingly popular due to the proliferation of computer-mediated learning environments (de Wever et al., 2006). In online environments, much interaction occurs through written communication. Even in the offline environment, having students write their answers reduces the burden and cost associated with transcribing. However, it should be noted that talking usually takes place much faster than writing and is more likely to match the speed of thought. In addition, participants are more likely to edit and censor their written responses than their speech. If research questions are not about a detailed, ongoing collaborative process of learning and group work, it would probably be acceptable to collect written verbalizations. When research questions require a detailed analysis of ongoing collaborative processes or representational changes, however, it is appropriate to avoid written transcripts unless it is unavoidable (e.g., computer-mediated interaction).

Although coding can be and is carried out directly from audio- or videotapes (Meier, Spada, & Rummel, 2007), recordings of verbal interaction are typically transcribed before coding. When transcriptions are made, they typically include not only the words spoken, but other linguistic and nonlinguistic information available on the tapes (e.g., pauses, sighs, facial expressions, change in intonations, etc.). One cannot transcribe all aspects of the interaction unless such details are useful for answering the research questions. Nonetheless, transcribing contextual information can be very helpful in interpreting the data. As researchers examine collaboration in online environments, student actions with respect to the technological tools often play an important role in interpreting student interaction and learning process. Such actions can also be transcribed and analyzed in the same fashion as verbal data (Jeong et al., 2011).

Analytic strategies

Verbal analysis codes raw verbal utterances into analyzable and inferentially productive code. Deciding what to code and devising coding schemes are both theoretically and data-driven processes (see Chi, 1997, for more details on these two approaches for developing coding schemes). The exact decision regarding what and how to code depends on the research questions, but the following three analytic strategies can be considered. First, verbal utterances can be coded into categories that represent meaningful learning events or outcomes. Examples of coding categories are: whether students give or receive explanations (Webb, 1989); whether students requested information, evaluated task difficulty, or elaborated what their partner said earlier (Hogan et al., 2000); whether an idea is repeated and if so, whether it was repeated by the speaker or a peer (Barron, 2003); or whether a given online post qualifies for any of the features that distinguish three different discourse modes (van Aalst, 2009). Coding utterances into categories allows the researcher to determine whether or not the target events or activity occurred and if so, how often. Once utterances are coded into categories, researchers can examine the relationships among different codes and also apply appropriate statistical procedures.

The second strategy is coding utterances into a scale. This is to assign a numerical value to segments of verbal utterances to indicate the degree or strength of the concepts being coded. For example, van Aalst (2009) analyzed collaborative summary notes created by students and rated each note on a 4-point scale in terms of knowledge quality and significance of findings. Suthers and Hundhausen (2003) also used rating in combination of category coding in their examination of collaborative scientific reasoning. After first coding the learning transcripts using eight categories such as “evidential relations” or “epistemic classifications,” they further rated a subset of them using a 3-point scale in order to capture the fact that a certain evidential relation is more important than others and difficult to infer. When rating scales are used in verbal analysis, they are often used with the same kind of detailed coding schemes used for category coding. Coders do not merely rate the utterances in an intuitive manner, but specific coding guidelines are used for each value of the scale. After verbal utterances are coded into such a scale, they can then be subjected to statistical analysis.

In the third strategy, verbal data can be coded into event sequences or structural representations that capture students’ understanding or learning processes. This was carried out both to represent the learning processes and the contents of understanding. For example, Chi and Koeske (1983) asked children to name dinosaurs they knew and link them to various properties (e.g., eating plants). Verbal protocols were used to capture children’s knowledge about dinosaurs. If children mentioned two different dinosaurs in succession, those two were assumed to be linked in their minds. Dinosaurs’ properties were also similarly linked to dinosaurs. The frequency of mention was assumed to reflect the strength of that linkage in their minds. Note that some initial coding is necessary before it can be combined into structural representations. In the above example, researchers first coded the references to dinosaurs and whether they were mentioned together, but instead of tallying the frequency of utterances (e.g., how frequently tyrannosaurs are mentioned), the researchers constructed them into a networked representation. This analysis strategy was initially used to capture the structural properties of an individual's representation (see also the mental model analysis by Chi et al., 1994; Vosniadou & Brewer, 1992), but can also be used to capture the group processes. For example, Chinn et al. (2000) attempted to code argument structures into similar networked representations. Their analysis coded argument events such as claims, explicit warrants, and challenges into a structured network. Once verbal utterances are coded into structured representations such as argument networks, the representations can be compared quantitatively as well as qualitatively, by using measurements such as the numbers of nodes and links contained in the networks, the breadth and depth of the networks, or the extent to which arguments are supported by explicit warrants. Statistics can be applied as well.

Although most researchers develop coding schemes tailored for specific hypotheses, it is possible to use schemes developed in other studies (Azevedo et al., 2008) as well as coding schemes developed for general use. Meier et al. (2007) developed a rating scheme to assess the "quality" of collaborative interaction. It was developed partly in the context of medical problem solving in a video-conferencing environment, but aims to assess general collaboration quality along nine dimensions. Another example is the *Rainbow* scheme developed by Baker, Andriessen, Lund, van Amelsvoort, and Quignard (2007). The goal of this scheme is to determine the extent to which students actually engage in argumentative activities in online learning environments and consists of seven categories that represent key aspects of knowledge-based argumentative interaction. In using coding schemes developed in other studies, whether they are specific or general, researchers need to examine carefully what the scheme was designed for and whether it is appropriate to use it for the current study. A scheme developed to study asynchronous online collaboration, for example, may not be suitable for studying offline collaboration or collaboration mediated by different technologies. It might also be the case that the existing scheme is not detailed enough to address more fine-tuned nuances of collaboration that the current study aims to examine. In such cases, researchers need to adapt existing schemes or develop a new one from scratch so as to appropriately address the hypotheses of the current investigations.

CONCLUSIONS

Whenever there is a theoretical shift, there is a need to develop a method that can capture the newly proposed concepts and processes. Verbal analysis was initially developed when theories of problem-solving and knowledge representation developed. There was a strong need for a method that could capture various problem-solving steps, strategies, and representational changes. Verbal data analysis successfully met these demands. It captured the representational changes accompanying cognitive development and expertise and identified learning mechanisms such as self-explanation. As the theoretical focus shifts again, this time to accommodate the social constructivist nature of learning, researchers are again in need of methods that can accurately examine group cognitive processes and outcomes. Verbal analysis is particularly well suited to address these challenges, due in part to the abundance of verbal data collected during collaborative interaction. So far, verbal analysis has been useful in helping researchers to understand the precise effects of social interactions and some of the mechanisms responsible for the outcomes. With further conceptual advances in how to conceptualize group cognition, verbal analysis is expected to make greater contributions to the field.

Although the strengths and weaknesses of any single analysis method can be discussed at length, verbal analysis is not the only methodology that can contribute to our understanding of collaborative learning. In addition, researchers are increasingly becoming eclectic with regard to data collection and analysis methods. Mixed- or multimethod studies are becoming more common (Hmelo-Silver, 2003). The field is undergoing, not just a theoretical shift, but also a methodological shift. In this new research environment, one of the challenges researchers often face is how to align different methodologies. Reconciling differences in the mechanics of different analytic traditions is relatively easy. A more difficult challenge is reconciling the different epistemologies associated with different methodologies. Verbal analysis, with its firm roots in positivist tradition, systematizes and quantifies analyses in order to achieve objectivity and generality. On the other hand, in many of the qualitative analysis traditions, the goal is more to reveal meaningful patterns or demonstrate the strength of a metaphor, rather than to unearth objective and general reality. Reconciling such different views will not be easy, and yet the field needs to find ways for these different analytical traditions to coexist in meaningful ways. With significant progress both on the conceptual and the methodological fronts, it is expected that meaningful progress in our understanding will soon be possible.

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REFERENCES

Akkerman, S., van den Bossche, P., Admiraal, W., Gijselaers, W., Segers, M., Simons, R.-J., & Kirschner, P. (2007). Reconsidering group cognition: From conceptual confusion to a boundary area between cognitive and socio-cultural perspectives? *Educational Research Review*, *2*, 39–63.

Austin, J. R. (2003). Transactive memory in organizational groups: The effects of content, consensus, specialization, and accuracy on group performance. *Journal of Applied Psychology, 88*(5), 866–878.

Azevedo, R., Moos, D. C., Green, J. A., Winters, F. I., & Cromley, J. G. (2008). Why is externally-facilitated regulated learning more effective than self-regulated learning with hypermedia? *Education Technology Research Development, 56*, 45–72.

Azmitia, M. (1988). Peer interaction and problem solving: When are two heads better than one? *Child Development, 59*, 87–96.

Baker, M., Andriessen, J., Lund, K., van Amelsvoort, M., & Quignard, M. (2007). Rainbow: A framework for analyzing computer-mediated pedagogical debates. *International Journal of Computer-Supported Collaborative Learning, 2*, 315–357.

Barron, B. (2000). Problem solving in video-based microworlds: Collaborative and individual outcomes of high-achieving sixth-grade students. *Journal of Educational Psychology, 92*(2), 391–398.

Barron, B. (2003). When smart groups fail. *The Journal of the Learning Sciences, 12*(3), 307–359.
Berkowitz, M., & Gibbs, J. (1983). Measuring the developmental features of moral discussion. *Merrill-Palmer Quarterly, 29*, 399–410.
Brown, G., & Yule, G. (1983). *Discourse analysis*. Cambridge, England: Cambridge University Press.
Chan, C. (2001). Peer collaboration and discourse patterns in learning from incompatible information. *Instructional Science, 29*, 443–479.
Chi, M. T. H. (1997). Quantifying qualitative analyses of verbal data: A practical guide. *Journal of the Learning Science, 6*(3), 271–315.
Chi, M. T. H. (2006). Two approaches to the study of experts' characteristics. In K. A. Ericsson, N. Charness, P. Feltovich, & R. Hoffman (Eds.), *Cambridge handbook of expertise and expert performance* (pp. 21–30). Cambridge, England: Cambridge University Press.
Chi, M. T. H., Bassok, M., Lewis, M. T., Reimann, P., & Glaser, R. (1989). Self-explanations: How students study and use examples in learning to solve problems. *Cognitive Science, 13*, 145–182.
Chi, M. T. H., de Leeuw, N., Chiu, M., & LaVancher, C. (1994). Eliciting self-explanations improves understanding. *Cognitive Science, 18*, 439–477.
Chi, M. T. H., Feltovich, P. J., & Glaser, R. (1981). Categorizing and representation of physics problems by experts and novices. *Cognitive Science, 5*, 121–152.
Chi, M. T. H., & Koeske, R. D. (1983). Network representation of a child's dinosaur knowledge. *Developmental Psychology, 19*(1), 29–39.
Chi, M. T. H., Siler, S. A., Jeong, A., Yamauchi, T., & Hausmann, R. G. (2001). Learning from human tutoring. *Cognitive Science, 25,* 471–533.
Chinn, C. A., O'Donnell, A. M., & Jinks, T. S. (2000). The structure of discourse in collaborative learning. *The Journal of Experimental Education, 69*(1), 77–97.
Clark, H. H., & Schaefer, E. F. (1989). Contributing to discourse. *Cognitive Science, 13*, 259–294.
Coleman, E. B., Brown, A. L., & Rivikin, I. D. (1997). The effect of instructional explanations on learning from scientific texts. *The Journal of the Learning Science, 6*(4), 347–365.
de Wever, B., Schellens, T., Valcke, M., & van Keer, H. (2006). Content analysis schemes to analyze transcripts of online asynchronous discussion groups: A review. *Computers and Education, 46*, 6–28.
Dillenbourg, P., & Traum, D. (2006). Sharing solutions: Persistence and grounding in multimodal collaborative problem solving. *The Journal of the Learning Sciences, 15*(1), 121–151.
Ericsson, K. A., & Simon, H. A. (1993). *Protocol analysis: Verbal report as data*. Cambridge, MA: MIT Press.
Galantucci, B., & Sebanz, N. (2009). Joint action: Current perspectives. *Topics in Cognitive Science, 1*, 255–259.
Gee, J. P. (2005). *An introduction to discourse analysis: Theory and method* (2nd ed.). New York: Routledge.
Goodwin, C., & Heritage, J. (1990). Conversation analysis. *Annual Review of Anthropology, 19*, 283–307.
Greeno, J. G., & van de Sande, C. (2007). Perspectival understanding of conceptions and conceptual growth in interaction. *Educational Psychologist, 42*(1), 9–23.
Hmelo-Silver, C. E. (2003). Analyzing collaborative knowledge construction: Multiple methods for integrated understanding. *Computers and Education, 41*, 397–420.
Hogan, K., Nastasi, B. K., & Pressley, M. (2000). Discourse patterns and collaborative scientific reasoning in peer and teacher-guided discussions. *Cognition and Instruction, 17*, 379–432.
Holsti, O. R. (1969). *Content analysis for the social sciences and humanities*. Menlo Park, CA: Addison-Wesley.
Hutchins, E. (1995). *Cognition in the wild*. Cambridge, MA: MIT Press.
Jeong, H., Chen, W., & Looi, C. K. (2011). Analysis of group understanding in artifact-mediated discourse. In G. Stahl, H. Spada, & N. Myake (Eds.), *Proceedings of the 9th International Conference on Computer-Supported Collaborative Learning.* Hong Kong: International Society of the Learning Sciences.
Jeong, H., & Chi, M. H. (2007). Knowledge convergence and collaborative learning. *Instructional Science, 35*, 287–315.
Meier, A., Spada, H., & Rummel, N. (2007). A rating scheme for assessing the quality of computer-supported collaboration processes. *International Journal of Computer-Supported Collaborative Learning, 2*, 63–86.
Neuendorf, K. A. (2002). *The content analysis guidebook*. Thousand Oaks, CA: Sage.
Newell, A., & Simon, H. A. (1972). *Human problem solving.* Englewood Cliffs, NJ: Prentice Hall.
Nisbett, R. E., & Wilson, T. D. (1977). Telling more than we can know: Verbal reports on mental processes. *Psychological Review, 84*(3), 231–259.
Okada, T., & Simon, H. A. (1997). Collaborative discovery in a scientific domain. *Cognitive Sciences, 21*(2), 109–146.
Resnick, L. B., Levine, J. M., & Teasley, S. D. (Eds.). (1991). *Perspectives on socially shared cognition*. Washington, DC: American Psychological Association.

Rummel, N., & Spada, H. (2005). Learning to collaborate: An instructional approach to promoting collaborative problem solving in computer-mediated settings. *The Journal of the Learning Sciences, 14*(2), 201–241.

Sacks, H., Schegloff, E., & Jefferson, G. (1974). A simplest systematics for the organization of turn-taking in conversation. *Language, 50*(4), 696–735.

Scardamalia, M., & Bereiter, C. (2006). Knowledge building: Theory, pedagogy, and technology. In R. K. Sawyers (Ed.), *Cambridge Handbook of the Learning Sciences* (pp. 97–115). New York: Cambridge University Press.

Schooler, J. W., & Engstler-Schooler, T. Y. (1990). Verbal overshadowing of visual memories: Some things are better left unsaid. *Cognitive Psychology, 22*(1), 36–71.

Shirouzu, H., Miyake, N., & Masukawa, H. (2002). Cognitively active externalization for situated reflection. *Cognitive Science, 26*, 469–501.

Simon, D. P., & Simon, H. A. (1989). Individual differences in problem solving physics problem. In H. A. Simon (Ed.). *Models of thought. Volume II* (pp. 215–231). New Haven, CT: Yale University Press. (Original worked published 1978)

Stahl, G. (2006). *Group cognition: Computer support for building collaborative knowledge*. Cambridge, MA: MIT Press.

Stegmann, K., Weinberger, A., & Fischer, F. (2007). Facilitating argumentative knowledge construction with computer-supported collaboration script. *International Journal of Computer-Supported Collaborative Learning, 2*, 421–447.

Suthers, D. D., & Hundhausen, C. D. (2003). An experimental study of the effects of representational guidance on collaborative learning processes. *The Journal of the Leaning Sciences, 12*(2), 183–218.

Teasley, S. D. (1995). The role of talk in children's peer collaborations. *Developmental Psychology, 31*(2), 207–220.

van Aalst, J. (2009). Distinguishing knowledge-sharing, knowledge-construction, and knowledge-creation discourse. *International Journal of Computer-Supported Collaborative Learning, 4*, 259–287.

Vosniadou, S., & Brewer, W. F. (1992). Mental models of the earth: A study of conceptual change in childhood. *Cognitive Psychology, 24*, 535–585.

Webb, N. M. (1989). Peer interaction and learning in small groups. *International Journal of Educational Research, 13*, 21–40.