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Cognitive Convergence in Collaborative Learning

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Abstract: Collaborative learning, as both a pedagogical method and a cognitive mechanism plays a prominent role in the Learning Sciences. In this symposium we will use the term "cognitive convergence" to encompass various concepts that have been used to explain the important processes underlying successful collaboration, such as intersubjectivity, co-construction, knowledge convergence, common ground, joint problem space, and transactive reasoning. The goal of the symposium is to contribute to a better understanding of the mechanisms of cognitive convergence and to relate cognitive convergence to individual learning outcomes. We include studies that emphasize detailed analyses of the mechanisms, provide ideas about how to conceptualize and measure convergence, and include qualitative and quantitative measures of shared and converging learning outcomes. A special emphasis will be on methodological questions about how to analyze the processes of achieving convergence and how to assess how convergence affects outcomes of collaborative learning.

Symposium Overview

Collaborative learning, as both a pedagogical method and a cognitive mechanism plays a prominent role in the Learning Sciences. Over the past 20 years, numerous studies have looked at the process of collaboration and provided evidence to address the question, "When are two heads better than one?" (Azmitia, 1988). In this symposium we will use the term cognitive convergence to encompass various concepts that have been used to explain the important processes underlying successful collaboration, such as intersubjectivity (Bell, Grossen, & Perret-Clermont, 1985), co-construction (Damon & Phelps, 1989), appropriation (Rogoff, 1990), common ground (Clark & Brennan, 1991), joint problem space (Teasley & Roschelle, 1993), transactivity (Teasley, 1997), and knowledge convergence (Fischer & Mandl, 2005; Jeong & Chi, 2007). We employ "cognitive convergence" to provide a construct with which to integrate and clarify the assortment of terms previously used and, in doing so, provide a better framework for understanding how and when collaboration leads to individual learning.

We believe it is important to move our understanding of collaborative learning forward because despite the popularity of this paradigm, research examining converging cognitive processes during collaboration have not necessarily shown that these processes can lead to better individual outcomes nor guarantee that all group members will demonstrate the same learning outcomes. For instance, studies from group decision making (e.g., Schultz-Hardt, Frey, Lüthgens, & Moscovici, 2000) have shown that an individual adapting to other group members might abandon their own more effective strategies to tackle the problem. In cases where a group has to include as many of the available knowledge resources as possible, it might be even good for the group level outcome if the individuals diverge with respect to the process of collaboration (Schultz-Hardt et al., 2000). Research on team mental models indicates that different levels of shared knowledge are required for teams to perform optimally in different kinds of tasks (Klimoski & Mohammed, 1994). So far, there is little empirical evidence with respect to these relations in the context of learning. First, it is not clear how much sharing of knowledge is needed to collaboratively learn in different collaborative learning scenarios. Moreover, there is only little empirical evidence that learners' highly similar outcomes (i.e., a high amount of shared knowledge) are accompanied by good collaborative learning in terms of individual learning outcomes (Jeong & Chi, 1999), although there has been some effort in the learning sciences towards understanding the cognitive and social mechanisms of convergence and knowledge sharing in collaborative learning environments (Barron, 2000; Roschelle & Teasley, 1995; Stahl, 2006). This work has led to identifying some important interindividual processes or mechanisms in collaborative scenarios, like coordination and convergent conceptual change, and provides starting points for systematic empirical research.

In contrast to the promising scope of theoretical approaches to phenomena of shared cognition (e.g., Resnick, Levine & Teasley, 1993) as well as to the wealth of empirical evidence from studies on social cognition (e.g., Thompson & Fine, 1999), evidence related to individual knowledge acquisition is rare. Main goal of this symposium is therefore to contribute to a better understanding of the mechanisms of cognitive convergence, but moreover, to relate cognitive convergence to individual learning outcomes. In addition, a focus of the symposium will be on the question of instructional interventions and their effect on cognitive convergence. We include studies that (a) emphasize detailed analyses of the mechanisms and (b) provide ideas how to conceptualize and measure cognitive convergence. In all of the contributions, special emphasis will be on methodological questions about how to analyze the processes of sharing and convergence and how to assess convergence (or divergence) and shared knowledge as outcomes of collaborative learning.

To address these issues the symposium includes the following papers:

Paper 1 focuses on conditions and effects of mutual modelling during collaborative learning. One main finding from these studies is that knowledge of the learning partners is indeed mutual, i.e. it can be predicted from what A knows about B, what B knows about A. In addition, the studies included in paper 1 show that design aspects of the collaboration environment (scripts and awareness tools) can substantially change mutual modelling.

Paper 2 suggests a complex systems perspective to analyze emergent convergence in online discussion groups. The authors conceptualize convergence from an emergentist conception of group collaboration assuming that macro-level behaviors emerge from and constrain micro-level interactions of individual group members. A specifically significant finding is that groups converge rather quickly in the first phases of interaction, which implies specific scaffolding strategies for online groups.

Paper 3 conceptualizes knowledge convergence from a cognitive perspective and analyzes joint explanations and co-constructions as main sources of cognitive convergence. An important finding is that co-constructions and joint explanations in spite of their theoretically crucial role for collaboration are rather rare in empirical data sets. The authors, however, identify situational characteristics under which these events occur with an increased frequency. As these situational characteristics can be changed by the instructional design of the collaboration environment, these findings suggest interventions to support co-construction.

Like paper 3, *Paper 4* provides a cognitive conceptualization and a methodology to assess knowledge convergence. It adds an instructional focus on how collaboration scripts aiming at stimulating controversial discussions might affect convergence. A main finding of this study is that group members strongly diverge *during* and share more knowledge *after* such kind of scripted collaboration.

Paper 1: How Do Co-Learners Know They Have Different Knowledge?

Pierre Dillenbourg

There is something intrinsicly differential in knowing: "warm" cannot be learned without "cold." The "stereoscopic" nature of learning is amplified in collaborative learning. Co-learners naturally come with different knowledge. Indeed, some methods, called macro-scripts, exploit natural differences within teams or induce new ones. Through the collaboration, some differences will be tackled and might disappear, but new differences will also appear. Divergence/convergence of knowledge been tackled under different notions such as socio-cognitive conflict (Doise & Mugny, 1984) or shared understanding (Roschelle & Teasley, 1995), which can be seen respectively as the half-empty and half-full bottle. Of course, there is no full bottle, i.e. no state of perfectly shared knowledge; it is only shared enough to fulfil the task (Clark & Schaeffer, 1989). What matters is not the percentage of shared knowledge, but the dynamics of the overcoming differences and discovering new ones. Obviously, this two-fold process requires that co-learners find out at some point that they have different knowledge or viewpoints. Knowing what one's partner knows or does not know is what we refer to as "mutual modelling." This term does not presume that learners maintain an explicit and accurate model of their partner but that some representation of the partner is used, even rudimentary, on-demand and temporary.

This contribution builds on five empirical studies on mutual modelling in dyads and triads. The mutual model is assessed by asking to A what B feels (study 1), what B will do (study 2), with B has one (study 3) or how much B knows about the domain (studies 4 & 5). The accuracy of this mutual model, hereafter referred to as MM-accuracy, is assessed by comparing A's answers to either what B actually did (studies 1 &2) or B's score at a knowledge test. We found that the accuracy of A's model of B was significantly correlated to the accuracy of B's model of A (Sangin et al, 2007) in most cases. We interpreted this correlation as an indication that the quality of mutual modelling depends less upon some individual attitude (some people would pay a greater attention to their partner) than to the quality of the team interactions.

In study 1, the independent variable "audio only" versus "audio+video" had no significant effect on MM-accuracy concerning emotions. In study 5, the independent variable was the use of a JIGSAW script. We hypothesized providing students with clearly identified subsets of knowledge would facilitate the fact of knowing who knows what. This effect was not confirmed. In the 3 other studies, the independent variable was the use of an awareness tool providing A with knowledge about B's viewpoint (study 2), location (study 3) or knowledge (study 4). The effect of the awareness tool on MM accuracy was partial in study 2 and significantly positive in study 4, but significantly negative in study 5. Regarding the dependent variables, MM accuracy did not predict a higher team performance or learning gains in studies 3 and 5, but was positively related to pre-test/post-test gains in study 4. In this study, MM-accuracy was statistically mediating the effect of the independent variable (awareness tool) on the dependent variable (learning gains).

These results do not converge very well, namely because mutual modelling interferes with other cognitive mechanisms such as information overload (displaying permanent information) or split-attention effect, as well as social mechanisms such as social comparison (knowing that my partner is more knowledgeable than me triggers various reactions). The study of mutual modelling is indeed complex from the methodological viewpoint: asking A about what B knows introduces a bias since it triggers more modelling than what would naturally occur. We are now complementing this approach by using two eye tracking machines in order to model how A and B observe each other's actions.

Paper 2: Convergence in Synchronous, Small-Group Discussions

Manu Kapur

In this presentation, I will report on a study that explores convergence in group discussions as an emergent behavior arising from theoretically-sound yet simple rules to model the collaborative, problem-solving interactions of its members (agents). Findings suggested that the organization of a group discussion into a convergent or a divergent regime (or attractor) was highly sensitive to the initial exchange between group members, including how inequities in participation evolved over time.

An emergentist conception of group collaboration (Arrow et al., 2000) necessitates an understanding of how macro-level behaviors emerge from and constrain micro-level interactions of individual agents. Understanding the “how,” however, requires an understanding of how simple rules at the local level can sufficiently generate complex emergent behavior at the collective level (Bar-Yam, 2003). For example, consider the brain as a collection of neurons (agents). These neurons are complex themselves, but exhibit simple binary behavior in their synaptic interactions. This type of emergent behavior, when complexity at the individual-level results in simplicity at the collective-level, is called emergent simplicity (Bar-Yam, 2003). Further, these simple (binary) synaptic interactions between neurons collectively give rise to complex brain "behaviors"—memory, cognition, etc.—that cannot be seen in the behavior of individual neurons. This type of emergent behavior, when simplicity at the individual-level results in complexity at the collective-level, is called emergent complexity (Bar-Yam, 2003).

The distinction between emergent simplicity and complexity demonstrates that a change of scale (individual vs. collective level) can be accompanied with a change in the type (simplicity vs. complexity) of behavior. We do not necessarily have to seek complex explanations for complex behavior; complex collective behavior may very well be explained via simple, minimal information, e.g., utility function, decision rule, or heuristic, contained in local interactions. Repeated updating, interaction, and aggregation of local interactions can sufficiently generate the phenomenon from the “bottom up” (Kapur, Voiklis, & Kinzer, 2007).

The concept of emergent simplicity was invoked to hypothesize a set of simple rules. Each interaction has an impact that:

i. moves the group towards a goal state, or
ii. moves the group away from a goal state, or
iii. maintains the status-quo (conceptualized as a "neutral impact").

Then, convergence in group discussion was conceived as an emergent complexity arising from these simple-rule-based interactions. The set of simple rules were operationalized as a one-dimensional Markov walk (Ross, 1996). Quantitative content analysis was then used to apply the Markov model to the discussions. In my presentation, I will use discussion episodes to illustrate how the simple rules attempt to model the co-evolution of telic and intersubjective convergence in problem-solving groups.

Research Context and Data Collection

Participants included sixty 11th-grade students from the science stream of a co-educational, English-medium high school in Ghaziabad, India. They were randomized into 20 triads and instructed to collaborate and solve well- and ill-structured problem scenarios in Newtonian Kinematics. Group members communicated with one another only through synchronous, text-only chat. The 20 automatically-archived transcripts contained the group discussions as well as their solutions, and formed the data used in our analyses.

Results and Discussion

The study revealed novel insights into the process of collaboration. The first insight concerned the differential impact of member contributions in a group discussion—high (low) quality contributions have a greater positive (negative) impact on the eventual outcome when they come earlier than later in a discussion. A corollary of this finding was that group discussions tended to organize themselves into convergence attractors (with high or low fitness) fairly quickly. Second, temporal analysis of the evolution of participation inequity in the group discussions suggested that participation levels also tended to get locked-in relatively early on in the discussion. This was consistent with the convergence finding. Because a lock-in of participation levels also implied a lock-in to the dominant members' proposals, high (low) quality contributions had a greater positive (negative) impact on group performance (quality of solution produced by the group) when they came earlier than later in a discussion. This is not to say that contributions made later in a discussion were not important. Instead, once a discussion got locked in, it seemed to organize itself into self-perpetuating attractors (Bar-Yam, 2003), making it increasingly difficult for member contributions to make an impact commensurate with their quality. Thus, both participation inequity and convergence analyses suggested a high sensitivity to the initial exchange; both significantly predicting the eventual group performance. Sensitivity simulation analysis revealed that eventual group performance could be statistically predicted based on what happened in the first 30-40% of a discussion.

These insights are significant. They bear important implications for scaffolding small-group discussions to achieve optimal outcomes. For example, if one's interest is primarily in maximizing group performance, the insight suggests a need for scaffolding early in the discussion as opposed to blanked scaffolding of the entire discussion, since the impact of early interactional activity on eventual group performance seems to be greater. Finally, the findings also underscore a methodological implication for paying particular attention to the temporal aspects of interactional dynamics; studying the temporal evolution of interactional patterns (convergence and participation inequity) can be insightful, presenting counterintuitive departures from assumptions of linearity in the problem-solving process.

Paper 3: Co-Construction and Joint Explanations

Michelene Chi

Knowledge convergence is the process by which two or more people share mutual understanding through social interactions (Brown & Campione, 1996; Hutchins, 1991; Resnick, Levine, & Teasley, 1991; Rogoff, 1998; Webb & Palinscar, 1996). There are three distinct but related aspects to consider in exploring the concept of knowledge convergence.

The first aspect is the process of convergence. That is, how do the processes of collaborating enable knowledge convergence? The process of convergence is often studied in the context of grounding (Clark & Brennan, 1991). When a contribution is made in dialogues, it needs to be grounded, meaning that the speaker and/or the listener need to believe that her partner understands her contribution and/or she understands her partner's contribution. Understanding the processes of grounding involves describing what the collaborating participants are actively doing, such as seeking evidence of understanding by asking questions or requesting repairs (e.g., 'did you mean this?'), or providing understanding by continued attention with acknowledgement. However, analyzing the grounding processes may capture only local convergence; grounding itself may not necessary lead to global convergence in terms of the speaker and listener's mental models (Chi, Siler & Jeong, 2004).

A second aspect of knowledge convergence is the resulting outcome, sometimes referred to as mutual understanding. One definition for this outcome is an increased similarity in the cognitive representations of the group members (Roschelle, 1992). For example, Roschelle (1992) analyzed the dialogues of a pair of high school students as they collaborated to learn the concepts of velocity and acceleration in physics. The outcome of their collaborating is convergence, in the sense that the collaborating students' representations became increasingly similar. Alternatively, the outcome of the process of grounding is that contributions become part of "common ground" or mutual knowledge (that is, an awareness of what others know, Clark & Brennan, 1991). There are other definitions of "mutual", "joint", or "socially shared" understanding as outcomes, such as "team mental models" (e.g., Cannon-Bowers, Salas, & Converse, 1993), "shared mental model" (Jeong & Chi, 2007), "group mind" (e.g., Bar-Tal, 1990), or "community memory" (Orr, 1990).

A third aspect of the knowledge convergence concept is the source of convergence, which is related to the process aspect of convergence. Research that focuses on the process of convergence typically describes many aspects of the process, whereas by source, we mean the parts of the processes that can be identified as the cause or origin of the convergent outcome. Researchers have assumed that the outcome of convergence (whether it is referred to as shared knowledge, mutual understanding or group mind) emerged as a result of group interactions. During collaborative interaction, it is assumed that partners jointly interpret a situation, coordinate their understandings, and come up with a solution to a problem together. The assumption is that as a result of such joint construction activities, convergence would arise.

Our work has been focusing on co-construction or joint explanation aspect of interactions, assuming that co-construction is responsible for convergence. We will discuss three ways that we have defined and coded co-construction, across three sets of data. The strictest definition requires coding of joint explanations that produce new knowledge that neither partner knew a priori. With such a strict definition, we found that the frequency of co-construction in general is typically low. Even with a low frequency, co-construction can be a powerful interaction process as it (by our definition) produces new knowledge that neither partner of the participating dyads knew. However, we will also talk about a unique situation under which the frequency of joint explanations between collaborating partners is high, and how we can utilize such a situation for instruction. This is a situation in which dyads are actively observing videos of other dyads interacting in a learning dialogues.

Paper 4: Knowledge Convergence: A Study on the Effects of Collaboration Scripts

Frank Fischer, Armin Weinberger, & Karsten Stegmann

Do learners in CSCL environments converge with respect to their knowledge by learning together? It has been argued, that such a convergence could be seen as the very motor of collaborative learning (Roschelle, 1992). However, studies show, that cognitive convergence in terms of sharing knowledge after collaboration is typically surprisingly low (Fischer & Mandl, 2005; Jeong & Chi, 2006). Moreover, research on knowledge convergence currently suffers from a lack of systematic conceptualisation and thus, operationalization, of the convergence construct. We used the framework of Weinberger, Stegmann and Fischer (2007) to conceptualize knowledge convergence: Knowledge equivalence refers to learning partners are similar with regard to the extent of their individual knowledge. Prior knowledge equivalence alludes to learners in a group possessing a similar degree of knowledge regarding a specified subject prior to collaborative learning, regardless of the specific concepts constituting knowledge content. During collaboration, knowledge contribution equivalence represents how much and how heterogeneously learners participate in discourse. With regard to knowledge acquisition, outcome knowledge equivalence of learners allows analyses to what extend two or more learners benefit similarly. Knowledge sharing is entailing that learners explicate their knowledge in contributing ideas to the discourse and that other learners integrate these ideas into their own lines of reasoning. Therefore, two complementary measurement approaches have been developed, namely the knowledge level approach and the transactivity approach (cf. Weinberger, Stegmann, & Fischer, 2007). The knowledge level approach to analyzing knowledge convergence processes proposes that individual contributions in which learners externalize knowledge be identified and compared and the extent of knowledge sharing subsequently determined. Shared prior knowledge refers to the knowledge of specific concepts that learners within a group have in common prior to collaborative learning. Knowledge sharing in discourse represents the share of similar concepts and ideas to discourse. Collaborative learners may acquire shared outcome knowledge, i.e. individual learners of one group possess knowledge on the same specific concepts after collaboration. The transactivity approach suggests analyzing the degree to which learners refer and build on others' knowledge contributions (Teasley, 1997).

Scripting. We applied this conceptualization to re-analyze data from an experimental study on collaboration scripts (Weinberger, Ertl, Fischer & Mandl, 2005). Collaboration scripts are instructional interventions that specify and cluster learning activities, organize them in roles and assign and sequence these roles in groups (Kollar, Fischer & Hesse, 2006). In this study, a "social" script was implemented into a CSCL case discussion environment aiming at enhancing the divergence in discourse (by assigning the roles of analysts and critics with additional prompts) and learning outcomes. The results of this study had shown that indeed the script increased learning outcomes. However, knowledge convergence has not been systematically analyzed with respect to these data. It is therefore unclear, to what extent learning partners really assumed the opposing roles and brought in diverging ideas and standpoints, and to what extent they benefited to a similar extent, and shared knowledge after collaboration.

Research Questions. We are going to examine the research questions (RQ1) to what extent the social script influences knowledge equivalence, knowledge sharing, and transactivity during collaborative learning and (RQ2) to what extent the social script supported outcome knowledge equivalence and shared outcome knowledge.

Methods

In this study, learners (N=48) were to learn to apply a psychological theory by analyzing and discussing three problem cases via a web-based discussion board. The subjects were randomly assigned to groups of three, which were in turn randomly assigned to one of two experimental conditions (with vs. without social script). Post hoc, a comparison between real and nominal groups (as used by Fischer & Mandl, 2005 and Jeong & Chi, 2006) was performed by randomly assigning all participants to nominal groups of three, comprising participants who had experienced the same collaborative learning environment, but who had collaborated with other participants. We varied the between-subject factor "social script" (with vs. without) and independently compared real to nominal groups as within-subject factor in order to account for the fact that learners were both members of real groups as well as members of nominal groups. Furthermore, we controlled for prior knowledge equivalence as well as shared prior knowledge. All results reported in the following are based on testing of hypotheses with ANOVA and t-test procedures.

Assessing knowledge convergence. The assessment of the convergence measures bases on analyses of the knowledge pre-test, the online discussion of cases, and the knowledge post-test. First, learners' written texts were segmented into propositional units consisting of concept-case relations (87% inter-rater agreement). In assessing application-oriented knowledge, we coded how the concepts from theory were adequately related to different problem case information. *(1) Knowledge equivalence*. To measure knowledge equivalence, the coefficient of variation has been calculated. The advantage of this measure is that it is normalized and therefore circumvents the production of an arithmetical artefact. This measure was calculated for the *(a) prior knowledge equivalence* (pre-test), the *(b) knowledge contribution equivalence* (discourse), and the *(c) outcome knowledge equivalence* (post-test). High knowledge equivalence scores may indicate either knowledge convergence or the "convergence of ignorance", i.e. that learners equally do not know how to apply specific concepts. *(2) Assessing shared knowledge.* To determine, to what degree learners know the same concepts, the amount of pairs of learners that applied the same concept were computed. This was performed for the *(a) shared prior knowledge* (pre-test), the *(b) sharing knowledge* (discourse), and the *(c) shared outcome knowledge* (post-test). *(3) Assessing transactivity*. The segments derived from the discourse analyses were coded with respect to different social modes of co-construction (cf. Weinberger & Fischer, 2006). Inter-rater reliability regarding the analysis of the social modes of co-construction amounted to $\kappa = .81$, measured with Cohen's Kappa.

Results and Conclusions

The study aimed to investigate the effects of a social script on knowledge convergence in computer-supported collaborative learning. The model study revealed that the knowledge convergence measures are sensitive to script effects as well as to comparisons of real vs. nominal groups. Results regarding RQ 1 (process convergence) indicate that the social script could support knowledge divergence processes, i.e. learners with the script contribute their ideas to a different extent and contribute different and possibly complementary concepts to the discussion. Members of small groups with the script contributed more divergently than learners without the script (knowledge contribution equivalence). In comparison, these groups also did not focus on the same concepts and were more dissimilar with regard to knowledge sharing. With respect to RQ 2 (outcome convergence), there is evidence that scripted learners shared more knowledge subsequent to collaborative learning than learners without the social script (shared outcome knowledge). As assumed, the social script facilitated knowledge divergence processes and shared outcome knowledge (De Lisi & Goldbeck, 1999). However, the script did not affect outcome knowledge equivalence, with one or two learners having acquired substantially more knowledge individually than their learning partners. Moreover, knowledge sharing and shared outcome knowledge seem to be strongly connected to learning together in real groups, as opposed to learning within the same learning environment. Real groups, however, demonstrated lower outcome knowledge equivalence in comparison to nominal groups. This last result supports the notion that learners within small groups can benefit from collaborative learning to substantially different degrees (Webb, et al., 1986), even though the results further indicate that social interaction of collaborative learners results in more shared outcome knowledge than exposure to the same learning environment and material.

In summary, the approach applied in the current study seems to be feasible in encouraging divergence during the processes of collaborative learning with scripts in order to increase the probability of shared knowledge following collaboration. Learners construct shared knowledge through social interaction in which they critically argue together based on divergent knowledge, rather than because they are provided with the same learning material.

Discussant

Stephanie Teasley

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Introduction

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Paper 4

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