Knowledge convergence in collaborative learning: Concepts and assessment

Armin Weinberger, Karsten Stegmann, Frank Fischer

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Knowledge Convergence:

Concepts, Assessment, and a Model Study

Armin Weinberger

Knowledge Media Research Center, Tübingen, Germany

Karsten Stegmann

University of Tübingen, Germany

Frank Fischer

Knowledge Media Research Center, Tübingen, Germany

Armin Weinberger, Ph.D. and Prof. Frank Fischer, Research Unit on Collaborative Knowledge Building, Knowledge Media Research Center; Karsten Stegmann, Virtual Ph.D. Program „Knowledge Acquisition and Knowledge Exchange with New Media“, University of Tübingen.

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Armin Weinberger, Knowledge Media Research Center, Konrad-Adenauer-Str. 40, 72072 Tübingen (Germany), Telephone: ++49+7071 979 201, Fax: ++49+7071 979 200, Email: a.weinberger@iwm-kmrc.de

Abstract

In collaborative learning the question has been raised as to how learners in small groups influence one another and converge or diverge with respect to knowledge. This article conceptualizes knowledge convergence and further provides measures for its assessment prior to, during, and subsequent to collaborative learning. In an exemplary study in the field of computer-supported collaborative learning with forty-eight (48) locally distant participants in 16 groups of three, we apply these measures and analyze the extent to which a computer-supported collaboration script can affect knowledge convergence. The study provides evidence for the applicability and sensitivity of the proposed knowledge convergence measures. Findings demonstrate that the instructional support increased productive divergence during collaboration and convergent individual outcomes.

Keywords

Knowledge convergence, shared knowledge, collaborative learning, cooperative learning, computer-supported collaborative learning (CSCL), collaboration scripts

KNOWLEDGE CONVERGENCE: CONCEPTS, ASSESSMENT, AND A MODEL STUDY

Various collaborative learning approaches are based on the idea that learners influence one another when learning together (e.g., De Lisi & Goldbeck, 1999). One important aspect of this mutual influence is that knowledge is shared and converges through social interaction (Barron, 2003; Roschelle, 1996; Ickes & Gonzales, 1996). Knowledge convergence has been conceptualized as a group-level phenomenon describing how two or more individuals, in socially interacting, are or become similar with respect to their knowledge. Learners who converge in knowledge have been found to benefit more from collaborative learning than learners who did not (Fischer & Mandl, 2005).

In this article, we will introduce varying conceptualizations of knowledge convergence at different phases of collaborative learning. Moreover, we will propose corresponding knowledge convergence measures. Additionally, we will apply these measures in an exemplary CSCL study (model study) in order to illustrate their applicability and sensitivity with respect to instructional support.

Conceptualizing Knowledge Convergence

In collaborative learning, learners are typically supposed to construct knowledge by working on complex problems together, including individually contributing to solving the problem, partaking in discussion of the individual contributions, and arriving at joint solutions (Roschelle & Teasley, 1995). Within this collaborative process, learners may adopt ideas from their peers and after collaborating share (i.e., have in common) specific ideas. There are also indications, however, that learners may differentially benefit from learning together, depending on their individual prerequisites, and *diverge* in knowledge, i.e. individuals within a group are or become more dissimilar with respect to their knowledge (Webb, Ender, & Lewis, 1986). Knowledge convergence can be conceptualized differently at varying stages of collaborative learning. A main distinction can be made between knowledge equivalence and shared knowledge. *Knowledge equivalence* refers to learners becoming more similar to their

learning partners with regard to the extent of their individual knowledge. By *shared knowledge*, we mean that learners have knowledge on the very same concepts as their learning partners. As outlined in the following, knowledge equivalence and shared knowledge may relate to individual learning outcomes in different ways prior to, during, and subsequent to collaborative learning.

Prior knowledge and its distribution among group members

The similarity of knowledge prior to collaborative learning can be conceptualized in at least two differing, yet complementary ways. *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. A study by Fischer (2001) showed that dyads with low prior knowledge equivalence acquired more knowledge in unstructured discussions than dyads with high prior knowledge equivalence. This study further demonstrated that prior knowledge convergence may interact with specific instructional support methods, in this case computer-supported collaboration scripts. Learners in knowledge convergent dyads were substantially supported in their knowledge acquisition by a collaboration script structuring learner interaction by assigning the roles of explainer and listener. However, the same collaboration script seemed to be a hindrance for knowledge divergent dyads. These may have been able to apply effective interaction patterns for themselves. The script appeared to interfere with the spontaneously emerging interaction patterns in so far as it assigned the roles of explainer and listener without considering the individual learning prerequisites or the distribution of these prerequisites within the group.

A further way in which the similarity of knowledge prior to collaborative learning can be conceptualized is *shared prior knowledge*, which refers to the knowledge of specific concepts that learners within a group have in common. Collaborative learning is often based on the idea that learners possess different learning resources and *unshared prior knowledge*,

i.e. knowledge that their learning partner does not have. For instance, jigsaw scenarios of collaborative learning (Aronson, Blaney, Stephan, Silkes, & Snapp, 1978) require learning partners with complementary knowledge to share their knowledge in order to collaboratively accomplish a learning task. So far, studies on collaborative learning have taken individual prior knowledge into consideration, e.g., when controlling for randomization of participants. We suggest that the distribution of prior knowledge within small groups of learners also influences collaborative learning and therefore needs to be controlled for.

Knowledge convergence processes

Knowledge convergence can also be regarded as *processes* which take place during collaborative learning and which can be conceptualized in various ways. One approach is based on the idea that, within discourse, learners may contribute ideas to varying or similar extents (*knowledge contribution equivalence*). To-date, investigations have examined how much and how heterogeneously learners participate in discourse, e.g., by counting the number of turns that the learners took in a discussion, and whether learners' participation was on-task or off-task irrespective of the single ideas contributed to discourse (Cohen, 1994).

Knowledge convergence processes have also centred on the notion that learners may share knowledge through discussion (*knowledge sharing*), entailing that learners explicate their knowledge in contributing ideas within discourse and that other learners integrate these ideas into their own line of reasoning. Knowledge sharing can be a unidirectional process, , whereby learners construct knowledge conveyed to them by peers, teachers or learning material. There are indications, however, that learners particularly benefit from more mutual forms of knowledge sharing in collaborative learning, e.g., when learners are confronted with knowledge divergent to their own or when they share a focus in discourse and build on the contributions of their learning partners (see Barron, 2003; De Lisi & Goldbeck, 1999; Teasley, 1997).

In order to capture these different aspects of knowledge sharing, two complementary measurement approaches have been developed, namely the *transactivity approach* and the *knowledge level approach*. The *transactivity approach* suggests analyzing learners' social mode of co-construction, depicting how strongly and in what ways learners refer to the contributions of their learning partners (Teasley, 1997). Transactivity is the degree to which learners refer and build on others' knowledge contributions, and has been found to be positively related to individual knowledge acquisition in collaborative scenarios (Teasley, 1997). In completing tasks in which they are required to arrive at joint conclusions, learners may build on each others' contributions in different ways and to different degrees. A social mode with a relatively low level of transactivity is the *externalization* of new ideas, for instance in starting a discussion. *Elicitation* is a social mode using the learning partner as a resource, typically by asking questions. Furthermore, learners can also build a consensus in various ways, e.g. through *quick*, *integration-oriented* or *conflict-oriented consensus building* (Weinberger & Fischer, 2006). Whereas quick consensus building signifies the simple acceptance of those ideas which learning partners contributed and primarily serves the continuation of discourse, integration- or conflict-oriented consensus building is seen to mediate learners building on each others' reasoning and sharing knowledge. Conflict-oriented consensus building is regarded as one of the highest transactive social modes, requiring learners to refer to aspects of peers' contributions with which they disagree and provide modified or alternative ideas (Teasley, 1997).

The *knowledge level approach* to analyzing knowledge convergence processes proposes that individual contributions in which learners externalize knowledge in discourse be identified and compared and the extent of knowledge sharing subsequently determined. Unlike the transactivity approach, the knowledge level approach allows an analysis of the type of knowledge e.g. knowledge of the task and knowledge of the team, which must be shared in order to enhance effective team performance (see Cannon-Bowers & Salas, 2001).

A limitation of the knowledge level approach is, however, that it does not capture the dynamics of how learners construct shared knowledge. It is for example possible that single ideas are co-constructed across the flow of verbal utterances of two or more speakers in face-to-face discourse, whereas asynchronous discussion boards may result in learners contributing ideas in parallel.

Knowledge convergence outcomes

Knowledge convergence may also be considered an *outcome* of learning in small groups. Numerous approaches to collaborative learning highlight the idea that collaborative learners mutually influence the learning outcomes of their partners (e.g., De Lisi & Goldbeck, 1999; Roschelle, 1996). As a result of this reciprocal influence, groups of learners may have developed shared knowledge on which they could build in order to jointly solve future problems more efficiently (Cannon-Bowers & Salas, 2001). Simultaneously, educators might like to ensure that learners benefit equally from learning together. Apart from the collaborative learners' mutual influence, knowledge convergence outcomes can also be a result of being exposed to the same learning material. However, to date, only few studies have systematically considered knowledge convergence outcomes and empirically traced back knowledge convergence outcomes to the social interaction of learners within a group (Fischer & Mandl, 2005; Jeong & Chi, 1999). Collaborative learning may aim to facilitate different types of knowledge convergence outcomes. On the one hand, collaborative learners may acquire *shared outcome knowledge*, i.e. individual learners of one group possess knowledge on the same specific concepts after collaboration. On the other hand, collaborative learning could facilitate the *outcome knowledge equivalence* of learners, i.e. two or more learners benefit similarly from learning together. The few quantitative studies carried out in the field to date show that collaborative learners share surprisingly little knowledge within a specified area compared to that which they could potentially share after learning together, but typically

do so, because they have mutually influenced each other in social interaction (Fischer & Mandl, 2005; Jeong & Chi, 1999).

Knowledge Convergence Measurement and a Model Study

In the preceding section, we conceptualized various aspects of knowledge convergence. In this section we address how these may be measured and further present how and with what results these measures have been applied in an exemplary study.

In analyzing knowledge convergence according to the knowledge level approach, some preconditions must be taken into consideration. First, measures of knowledge convergence depend on what and how individual knowledge is being assessed. This dependency implies, for instance, that the analysis of knowledge convergence regarding single concepts assessed by traditional recall or multiple choice tests captures neither the convergence of understanding of these concepts nor the convergence of knowledge on how they are applied in different contexts. Learners may for example use the same technical terms in such tests, yet have a different understanding of their meaning and how they are applied to problem cases. In contrast, if knowledge is assessed in a meaningful context, whereby learners are asked to apply specific concepts to new and complex problems, knowledge convergence measures can indicate to what extent learners are similarly able to use and apply concepts appropriately in a given context. A further restriction of this approach is that the knowledge convergence measures are only valid for limited and well-specified areas of knowledge with a limited number of aspects which can be assessed empirically. In learning environments, this typically applies to the knowledge area that is to be learned given that it can be defined a priori and empirically analyzed a posteriori. Of course, convergence measures can be applied to any kind of cognitive response (Ickes & Gonzales, 1996) which can be specified and quantified. Learners may, for instance, acquire knowledge other than that which was initially targeted, i.e. the knowledge they are supposed to learn within a specific learning environment, and converge towards this non-target knowledge, which may well

include misconceptions. Furthermore, the specified knowledge area needs to be operationalized by different equivalent and independent knowledge items in order to provide a basis of comparison when it comes to learners' knowledge levels, i.e. the items to be learnt should thus be comparably difficult and equally important. Finally, to ensure that knowledge convergence outcomes are a consequence of social interaction, we must exclude alternative explanations, such as (1) *chance* by applying measures that are adjusted for chance concurrence, (2) *extremely high or low knowledge scores* which lead to an arithmetic artefact on the convergence scores, namely that learners who knew everything or nothing at all would simultaneously also have perfect knowledge convergence scores, by selecting knowledge items of medium difficulty, or (3) having been provided with the *same learning resources* and been exposed to the *same learning environment* by comparing real groups of learners who have actually collaborated with each other with nominal groups of learners who have learned collaboratively under the same conditions, but with different partners than those with whom they are being compared. Note that the use of nominal groups here differs from their traditional use in social psychology, where such groups consist of individuals working alone on a problem or task and the experimental focus consists of comparisons between group and individual performances. In the case of measuring knowledge convergence, however, nominal groups consist of individuals who collaborated, but did so with learning partners other than those to which they are assigned in a (post-hoc) nominal group. These requirements of the knowledge measures for assessing convergence do not apply when analyzing knowledge convergence with the transactivity approach.

In order to facilitate a better understanding of the different measures which we propose for the various phases of collaborative learning, the following section provides important background information regarding the exemplary study.

Background of the model study

In illustrating the methods of knowledge and knowledge convergence assessment applied in our model study, we aim to provide an example of how the requirements for knowledge convergence measurement delineated above can be met. Furthermore, the study should demonstrate the applicability of the convergence measures in CSCL and investigate the sensitivity of the measures for instructional support. Finally, the study aims to illustrate how measuring knowledge convergence can highlight the way in which the mutual influence of learners in social interaction is able to facilitate learning. In this CSCL study, learners were to learn to apply a psychological theory (attribution theory of Weiner, 1985) by analyzing and discussing three problem cases via a web-based discussion board, in which learners could read, write and exchange messages in text windows. We assumed that learners contributing divergent ideas to the asynchronous discourse and building on each other's contribution in a conflict-oriented manner would benefit more individually from the learning environment and would also share more knowledge after collaboration. The participation in the CSCL environment constituted part of an obligatory introduction course in Educational Science and the learning goal was part of the standard curriculum. The *sample* consisted of 48 first semester students of Educational Science at the University of Munich who were randomly assigned to groups of three, which were in turn randomly assigned to one of two experimental conditions (with vs. without a computer-supported collaboration script). *Computer-supported collaboration scripts* are to be understood as activity programs that specify, sequence, and distribute roles and activities to the individual learners within a group and that are implemented within a CSCL environment. In applying a so-called "social script" that assigned the roles of case analyst and constructive critic, we aimed to particularly facilitate the social mode of conflict-oriented consensus building, divergent knowledge contributions, shared outcome knowledge, and outcome knowledge equivalence. The computer-supported social script supported the above-named roles with specific prompts that were automatically inserted into the learners' text windows, e.g., THESE ASPECTS OF YOUR ANALYSIS ARE NOT

CLEAR TO ME YET:, and provided learners with a specific sequence for performing these roles. The case analyst first composed an initial analysis of the problem case. Following this, the two critics contributed critiques to which the case analyst was requested to reply. After another round of critiques, the case analyst wrote a final analysis which was supposed to take the preceding discussion into account. The script established role rotation, i.e. each of the three learners assumed the role of case analyst in one of the three problem cases and the role of constructive critic in the remaining two cases. While the social script proved effective in helping participants learn to apply Weiner's attribution theory (see Weinberger, Ertl, Fischer, & Mandl, 2005), the data collected have not yet been analysed with respect to knowledge convergence.

Post hoc, a comparison between *real and nominal groups* 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. Using a two-way ANOVA 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 the nominal groups. Furthermore, we controlled for prior knowledge equivalence as well as shared prior knowledge.

The *procedure of the study* included (1) a knowledge pre-test lasting 10 minutes, (2) a 15 minute individual learning phase, in which learners studied a three-page description of Weiner's attribution theory (1985), (3) a 20 minute introduction to the learning environment, and (4) a collaborative phase of 80 minutes, in which learners analyzed and discussed three problem cases based on Weiner's attribution theory, e.g. problem cases of students suffering from dysfunctional attribution patterns (see Appendix A). (5) Finally, participants analyzed a transfer problem case in an individual post-test (10 minutes).

The study is based on data collected in an earlier study, in which we analyzed the individual knowledge acquisition of collaborative learners (see Weinberger et al., 2005). In the present article, we investigate the effects of instructional support in the form of a computer-supported collaboration script on knowledge convergence processes and outcomes. We further investigate the effect of the mutual influence of learners in social interaction in real groups vs. being exposed to the same collaborative learning environment in nominal groups on knowledge convergence processes and outcomes.

Before turning to the specific research questions, we carried out a *randomization check*: To what extent did the experimental groups differ with respect to prior knowledge convergence? While there may not be differences between the experimental groups regarding individual prior knowledge, the groups of three may differ with respect to prior knowledge convergence.

The research questions (RQ) are as follows:

RQ 1: To what extent does a computer-supported collaboration script influence knowledge convergence processes during collaborative learning?

Expectations regarding RQ 1 are that the script will facilitate knowledge divergence processes as compared to an unstructured collaboration condition. Learners supported by the script are expected to contribute their knowledge to a different extent for one problem case due to the different roles imposed by the script (*knowledge contribution equivalence*) and are also expected to contribute complementary knowledge concepts (*knowledge sharing*). Due to the fact that the script induces conflicting roles, we also expect it to facilitate the highly transactive social mode of *conflict-oriented consensus building*.

The real groups are expected to score higher in knowledge sharing than the nominal groups, since learners in real groups are able to perceive and adopt specific knowledge concepts explicated by their learning partners during collaborative learning. Real groups may surpass nominal groups regarding knowledge contribution equivalence, on account of learners

in real groups being able to adjust to their learning partners in order to contribute more equally.

RQ 2: To what extent does a computer-supported script influence knowledge convergence outcomes as measured subsequent to collaborative learning?

The expectations regarding RQ 2 are that learners supported by the script will achieve more equivalent and shared outcome knowledge than learners without a script. Scripted learners are expected to converge towards shared knowledge, because they are guided towards engaging in transactive discourse and building on the knowledge contributions of their learning partners. Although the script assigns different roles within each problem case, the three learners of a group assume all possible roles distributed across the problem cases. We expect this role rotation of the script to help learners benefit more equally from collaborative learning.

We further hypothesize that real groups will attain more shared outcome knowledge than nominal groups, due to specific social interaction with their learning partners. No specific hypothesis could be formulated for outcome knowledge equivalence. Learners may either converge towards the mean of the real groups or may benefit differently from social interaction within the real groups.

Assessing individual target knowledge. Participants were to learn to analyze problem cases applying the attributional theory of Weiner (1985), which includes the concepts of stability and locality of attributions. According to Weiner (1985), attributions are either stable or instable and internal or external. The problem cases contained various attributions of a fictitious learner and other actors of educational relevance, such as teacher and parents (see Appendix A). The discussion surrounding each of the three individual problem cases which learners were required to analyze, provided the data for analysis of the collaborative phase. The task of the students in the collaborative phase was to apply the single concepts of the attributional theory to these pieces of case information. The same task was assigned in the

individual pre-test and post-test. The knowledge test score was formed by identifying the adequate concept-case relations constructed by learners as compared to expert solutions (see table 1). Concept-case relations that did not concern the target knowledge and did not match the expert solution were considered inadequate. First, learners' written texts were segmented into propositional units consisting of concept-case relations (87% rater agreement) i.e. the criterion for segmentation was the separation of units including concepts from attribution theory that could be evaluated as being true or false. For instance, in the sentence "The indication that no one in the family is witty is equivalent to an attribution concerning talent" the learner constructed the relation "is equivalent" between the concept "attribution concerning talent" and the problem information "that no one in the family is witty". Learners may also reflect on the theoretical concepts by linking two concepts (*construction of conceptual space*) or recap the problem respectively by linking two pieces of information of the problem cases together (*construction of problem space*; see Weinberger & Fischer, 2006). In assessing application-oriented knowledge, we focused on concept-case relations and blind-coded how between 5 and 7 concepts (depending on the case) could be adequately related to different problem case information on the basis of a list of concept-case relations that experts had constructed beforehand. These concepts were locality and stability (see table 1) as well as concepts of contributions of self and contributions of other (see Weiner, 1985) as they applied to the specific problem cases.

Assessing prior knowledge equivalence

In general, measures of dispersion can be used to analyze differences in prior knowledge between learners (see Ickes & Gonzales, 1996). However, most of the measures used, such as for example standard deviation, are dependent on the values they are derived from, so that extremely high or low individual knowledge test scores arithmetically restrict convergence measures. In contrast, the *coefficient of variation* is defined as the standard deviation of a group divided by the group mean. Thus, the advantage of this measure is that it

is normalized and therefore circumvents the production of an arithmetical artefact. This measure can be applied in the following procedure for assessment of prior knowledge equivalence. First, individual prior knowledge scores must be calculated. These form the basis for measuring prior knowledge equivalence. Second, standard deviations of the knowledge scores of learners within one group are determined and then aggregated. This step is carried out because this measure of dispersion indicates the extent to which learners deviate and are thus dissimilar from the group mean. Third, in order to calculate the coefficient of variation, the aggregated standard deviations are subsequently divided by the mean.

For example in table 2, group A and group B both consist of three members and yield different prior knowledge equivalence values. In group A, each of the learners demonstrates knowledge in constructing two different concept-case relations. In group B, Tina knows how to construct three concept-case relations, whereas Thomas and Tim each know how to construct two concept-case relations prior to their learning together. Individual knowledge scores of each learner in group A was 2, thus resulting in a mean of 2 ($SD = 0$); in group B the scores are 3, 2, and 2 for Tina, Thomas, and Tim respectively. Group B has a mean of 2.33 ($SD = 0.58$). Prior knowledge in group A is more equivalent than prior knowledge in group B.

The prior knowledge equivalence measure is a relative measure that does not provide information about how much knowledge learners have acquired, since concepts that are not known by any of the group members also contribute to these convergence scores. In this way, high prior knowledge equivalence scores may indicate both knowledge convergence as well as the "convergence of ignorance", i.e. that learners equally do not know how to apply specific concepts.

Application of the measure in the model study. The model study provides an example for the convergence of ignorance. In the model study, approximately ¾ of the participants did not score in the pre-test and would thus demonstrate perfect prior equivalence of "ignorance" regarding the target knowledge. Due to this floor effect, however, prior knowledge could not

be reliably determined. Without reliable prior knowledge measures, the respective knowledge convergence measures could also not be reliably assessed. To nevertheless ensure randomization, we analyzed whether learners without prior knowledge were evenly distributed across the experimental groups ($\chi^2(3) = .29$, *n. s.*).

Assessing shared prior knowledge

Assessing shared prior knowledge centres on the idea of comparing learners' individual knowledge prior to collaborative learning. To examine whether learners possess knowledge of the same specific concepts, we suggest pair-wise comparisons of items of a prior knowledge test. In order to compare the knowledge of one learner with the knowledge of another learner, the specific concepts that learners know must first be assessed. Second, pair-wise comparisons are conducted by comparing all possible pairs of learners within small groups to determine to what degree learners know the same concepts. Third, any pair of learners within the small groups that shares the ability to apply a specific concept to a problem case adds to the shared prior knowledge score. Since the measure for shared prior knowledge is based on individual scores and due to the fact that individual learners may have little knowledge on the subject prior to collaborative learning, the measure for shared prior knowledge can be normalized by dividing it by the mean value of the group.

In groups of more than two members, knowledge may be unshared, partially shared, or completely shared (Klimoski & Mohammed, 1994). These states can be differentially weighted depending on the theoretical approach and research question. For instance, when all learners of one group of three are able to correctly respond to a knowledge test item, a shared prior knowledge value of 3 is credited to the learning group equalling three "positive" pair-wise comparisons. If only two learners are able to respond correctly to this item, a shared prior knowledge value of 1 is credited for one positive pair-wise comparison. In any other case, including a group mean of zero, a shared prior knowledge value of zero is assigned.

Application of the measure in the model study. Due to the fact that most participants of the study did not have any prior target knowledge (see above), we would like to refer back to the example provided in table 2. Group A would yield a shared prior knowledge value of 0, whereas in group B, the first concept-case relation is known by Tina and Thomas, Tina and Tim, and Thomas and Tim. The second concept-case relation is known by both Tina and Tim and the third is known by Tina and Thomas, which amounts to a shared prior knowledge value of 5 examining each pair of group B. Normalized by the group mean (m = 2.33), this leads to a value of 2.14. Group B shares numerically more prior knowledge as compared to group A.

Assessing knowledge contribution equivalence during collaboration

In order to measure knowledge contribution equivalence, knowledge externalized in discourse first needs to be identified. Once the knowledge contributed by individual learners during collaborative learning has been assessed, the procedure for measuring knowledge contribution equivalence remains the same as the procedure for measuring prior knowledge equivalence (see above): First, individual knowledge explicated by learners in discourse is identified. Second, the standard deviations of these knowledge scores within one group are determined and then aggregated. Third, the coefficient of variation is subsequently calculated.

Application of the measure in the model study. In the model study, the empirical maximum of the number of different concept-case relations constructed by learners in discourse during collaborative learning amounted to 7. The item difficulty in applying the single concepts during collaborative learning ranged from $p_{min} = .44$ to $p_{max} = .79$. The concept-case relations constructed in discourse were coded reliably (Cohen's $\kappa = .90$) and consistently (Cronbach's $\alpha = .83$). It was expected that, on account of their different roles within a single problem case, learners using the script would contribute their knowledge to a different extent during collaboration. Analysis shows that groups supported by the social script indeed yielded lower *knowledge contribution equivalence* scores (see table 3). As

expected, the script reduced knowledge contribution equivalence. This was found to be a significant and large effect, $F(1,14) = 13.09$, $p < .05$, $\eta^2 = .48$. Furthermore, due to the social interaction taking part in real groups, it was expected that learners would adjust the extent to which they contributed their knowledge during collaborative learning towards the group mean. However, *knowledge contribution equivalence* could not be traced back to the specific social interaction within individual small groups $F(1,14) = 0.39$, *n. s.,* i.e. real groups did not differ from nominal groups with respect to knowledge contribution equivalence. These results support the hypothesis that the social script facilitates knowledge divergence processes. However, they do not confirm that learners who interact with each other also show higher knowledge contribution equivalence.

Assessing knowledge sharing during collaboration

Knowledge sharing during collaboration can be assessed by analyzing the distribution of the individual knowledge that learners externalize in discourse (*knowledge level approach*) or by analyzing the transactivity of learners' social modes of co-construction (*transactivity approach*). In order to provide a more detailed example, the application of both approaches to an excerpt of scripted discourse is outlined in Appendix B.

Knowledge level approach

As in the measurement of knowledge contribution equivalence, the individual knowledge contributed by learners in discourse must first be identified. Following this, the measure for knowledge sharing is formed analogously to the measure for shared prior knowledge and is based on pair-wise comparisons of learners' contributions during collaborative learning. For each of the small groups of learners, it must be determined whether each possible pair used the same propositional units (concept-case relations). Each of those pairs adds to the knowledge sharing score. Finally, the score is normalized by dividing it by the mean value of the small group.

Application of the measure in the model study. Within the real groups of the model study, 50 % of knowledge was unshared, 30 % partly shared, i.e. shared between only two of the three group members, and 20 % of knowledge was shared by all three members in both the scripted and the unscripted conditions. With respect to knowledge sharing, groups supported by the social script scored lower (see table 3), which means that scripted learners contributed more divergent knowledge concepts in the discussions than learners without the script. This effect was found to be significant and large, $F(1,14) = 15.53$, $p < .05$, $\eta^2 = .53$. Real groups clearly scored higher in knowledge sharing than nominal groups, $F(1,14) = 47.63$, $p < .05$, $\eta^2 = .77$. This result strongly supports the claim that a large part of knowledge sharing can be traced back to the specific social interaction within real groups and cannot be explained to a large extent by learning under the same experimental conditions.

Transactivity approach

To analyze how learners build consensus in discourse, it has been suggested that discourse corpora first be sampled and segmented (see Weinberger & Fischer, 2006). Knowledge convergence must be assessed on the basis of coherent samples of discourse corpora in order to capture how learners relate to and operate on each others' knowledge contributions. Segmentation of discourse corpora must enable the analysis of learners' mutual references, at the same time as allowing the differentiation of single knowledge contributions upon which learners build consensus. Second, segments are to be coded with respect to different social modes of co-construction. Weinberger and Fischer (2006) distinguish five social modes characterized by different degrees of transactivity, namely externalization and elicitation as well as quick, integration-oriented, and conflict-oriented modes of consensus building. Externalization refers to learners contributing new ideas in the group without any reference to prior contributions of their learning partners. This applies for instance, to any initial contribution in a discussion, e.g., "Here is my first analysis of the problem case:". Elicitation denotes learners asking questions of their learning partners in order to induce a

reaction and use them as additional learning resources, e.g., “Do you think that this is a stable attribution?”. Quick consensus building is a low transactive social mode in which learners accept contributions of their peers without further modifications or comments, e.g. by saying “Ok, I agree”. It remains unclear whether learners who quickly build a consensus actually agree with the ideas explicated by their learning partners in discourse, or whether agreement is signalised for momentary purposes only, such as for example in order to move on with the task. The more transactive integration-oriented consensus building indicates the extent to which learners build on the ideas of their peers in discourse. Learners may adopt, integrate or apply knowledge that their learning partners have previously externalized, e.g., A: “Michael attributes to internal, stable causes;” B: “Ok, I have got that now. That means he attributes to talent and that is a detrimental attribution pattern”. Conflict-oriented consensus building has been argued to constitute an even higher transactive social mode and refers to learners disagreeing, modifying or replacing ideas externalized by their learning partners, e.g., A: “The attribution of the teacher is de-motivating;” B: “Wrong, the attribution of the teacher is beneficial”. Conflict-oriented consensus building indicates that learners strongly build on the contributions of their learning partners, at the same time as contributing new and different ideas themselves.

Application of the measure in the model study. In the model study, learners were required to analyze three problem cases. In order to reduce data, but nevertheless still be able to build on a coherent subset of discourse corpora, we sampled the total discourse corpora with respect to a discussion on one of the three problem cases. We segmented the discourse corpora with multiple granularities not only to capture the social modes of co-construction regarding single knowledge contributions, but also to capture how learners related to their learning partners (see Weinberger & Fischer, 2006). On average, 612.63 words (*SD* = 242.69) were posted in 12.44 messages (*SD* = 6.60) across the three web-based discussion boards. In the discussion of one of the three problem cases, each learner produced 16.71 propositional

units (*SD* = 12.79). Inter-rater reliability regarding the analysis of the social modes of co-construction within one of the three problem cases amounted to $\kappa = .81$, measured with Cohen's Kappa. Regarding conflict-oriented consensus building, scripted and unscripted groups were compared. Results show that learners supported with the script engaged in more conflict-oriented consensus building (*M* = 5.96, *SD* = 5.50) than learners without (*M* = 3.42, *SD* = 3.67), $t(46) = -1.88$, $p < .05$ (one-tailed). This result is in line with the results on knowledge contribution equivalence and knowledge sharing, whereby participants supported with the script more frequently disagreed, contributed more ideas which differed from those of their learning partners and thus diverged more with respect to the propositional units contributed during collaborative learning compared to learners who were not supported with the script.

Assessing outcome knowledge equivalence

As a result of learning together, learners may have acquired outcome knowledge equivalence. Assessing outcome knowledge equivalence is analogous to assessing prior knowledge equivalence and knowledge contribution equivalence. First, individual outcome knowledge needs to be measured reliably in individual tests following collaboration. Second, the coefficient of variation can be calculated for each small group of learners and aggregated to form a measure of outcome knowledge equivalence based on specific knowledge items of medium difficulty that learners can or cannot adequately respond to in knowledge post-tests.

Application of the measure in the model study. In the model study, the knowledge scale in the post-test was based on 5 items consisting of propositional units (concept-case relations) of medium difficulty ($p_{min} = .27$, $p_{max} = .40$) and was of sufficient reliability (Cronbach's $\alpha = .70$). In contrast to the expectation that the script should facilitate knowledge convergence outcomes, no effect of the script could be found with respect to outcome knowledge equivalence (see table 3), $F(1,14) = 2.73$, *n. s*. The results further show a large (though only marginally significant) effect indicating that the nominal groups yielded even

higher scores for outcome knowledge equivalence than learners within real groups, $F(1,14) = 3.45$, $p < .10$, $\eta^2 = .20$. Learners within real groups therefore do not appear to benefit equally from collaborative learning. Taking the descriptive data and the marginally significant but large effects into consideration, it is possible that effects could be found based on a larger number of participants, since group level analyses require more subjects than individual level analyses. Even though this study was conducted with 48 participants, for instance, only 16 groups of three could enter statistical analysis at the group level.

Assessing shared outcome knowledge

The measure of shared outcome knowledge is based on comparisons of different pairs of learners with respect to the adequacy of their responses to specific items in an individual knowledge test. As was the case with outcome knowledge equivalence, shared outcome knowledge needs to be controlled for influences other than the influence of social interaction during collaborative learning.

Application of the measure in the model study. Regarding shared outcome knowledge across all real groups in the model study, 50 % of knowledge was unshared, 34 % partly shared, i.e. shared only between two of the three group members, and 16 % of knowledge was shared by all three members of real groups. With respect to shared outcome knowledge, groups supported by the social script scored more highly (see table 3). This indicates that scripted learners possess more shared knowledge subsequent to learning together than learners without a script. This was found to be a large effect, which is marginally significant, $F(1,14) = 3.09$, $p = .10$, $\eta^2 = .18$. Shared outcome knowledge also seems to be a result of actually working together. Real groups attained higher scores of shared outcome knowledge than nominal groups, $F(1,14) = 4.92$, $p < .05$, $\eta^2 = .26$. These results support the hypotheses that both scripts and the specific social interaction in real groups facilitate shared outcome knowledge.

Discussion of the Results of the Model Study

First, the model study served to illustrate how and to what end the different knowledge convergence measures can be applied in a CSCL study. Measuring knowledge convergence has shown to serve as predictor for later outcomes of groups (Cannon-Bowers & Salas, 2001; Fischer & Mandl, 2005). Randomization of groups of learners, for instance, should thus not only be checked based on measurements of individual prior knowledge, but also on the distribution of prior knowledge within the learning groups. Second, the model 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 the RQs indicate that the social script could support knowledge divergence processes as expected, 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*. Furthermore, there is evidence that scripted learners shared more knowledge subsequent to collaborative learning than learners without the social script (*shared outcome knowledge*). As intended, 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.

From an educational perspective, the low knowledge contribution equivalence in discourse (i.e., learners did not equally contribute ideas to the discussion) and the low knowledge outcome equivalence (i.e., learners showed considerable differences in their ability to apply the new concepts individually after collaboration) might be seen as serious challenges. Since these measures have hardly been applied in investigations on collaborative learning to date, it remains unclear, whether various instructional approaches may yield different effects than those found in the present study.

Conclusion

Investigations involving collaborative learning have often focused on the individual learner and individual activities. However, theoretical approaches to collaborative learning emphasize the role of the learning partner and how the social interactions of learners influence knowledge construction (e.g., Barron, 2003). Investigating knowledge convergence prior to, during and subsequent to collaborative learning can help to test the theoretical assumptions of learners' mutual influence. It is obvious that multiple approaches to the analysis of knowledge convergence are needed at this early stage of convergence investigation in collaborative learning. Approaches based on the analysis of learners' social interaction can capture the processes involved in learners' co-construction and exchange of ideas, whereas approaches based on comparisons of learners' knowledge levels at given times can show how members of one and the same group benefit differently (or similarly) from collaborative learning. The

model study shows how instructional support may (beyond influencing individual learning) also influence the distribution of learners' contributions to discourse in small groups. Thus, in analyzing the way in which instructional support influences knowledge convergence in collaborative learning, we may learn how such support can be improved regarding effects on knowledge convergence and its influence on individual outcomes respectively. Furthermore, different theoretical approaches to collaborative learning do not only aim to support individual knowledge construction, but also the co-construction and convergence of knowledge (Roschelle, 1996). Applying these measures can help to fine-tune the support of knowledge convergence for collaborative learning. These measures can be used to evaluate theoretical assumptions and to consolidate findings of knowledge convergence in collaborative learning in future studies. Presently, the concept of knowledge convergence constitutes an important approach to understanding the mechanisms of collaborative learning and the measures suggested can be viewed as a starting point in establishing standards for their evaluation. Conversely, investigating knowledge convergence may encourage the development and refinement of theoretical assumptions with respect to collaborative learning.

Limitations of quantitatively assessing knowledge convergence. The approaches to the analysis of knowledge convergence presented here, are valid for testing hypotheses based on theoretical approaches to collaborative learning that predict learning outcomes based on the mutual influence of learners. For these theoretical approaches, the group level phenomena must be analyzed beyond comparisons of mean values at the individual level. In the following, several limitations of the presented measures are discussed, namely (1) the limitation of *knowledge as a specifiable quantity*, (2) the problem of *knowledge that is not externalized*, and (3) the *ambiguity of individual contributions to discourse*.

(1) The knowledge equivalence and the shared knowledge measures are limited to approaches that make assumptions on target *knowledge as a specifiable quantity*. The suggested knowledge convergence measures are based on content analysis of discourse and

written responses to open questions, the results of which are aggregated and quantified to assess individual knowledge. As of yet, there are no simple answers to the questions, what is knowledge and how can it be quantified? The operationalization of knowledge into discrete units may resemble an approximation of the construct rather than an unambiguous representation and yet, most of the presented knowledge convergence measures build on a quantification of knowledge. The presented knowledge convergence measures must be carefully interpreted depending on the way in which individual knowledge is being assessed. For instance, given that learners are able to recall the same specific concept in a free recall test, they may still possess divergent understanding of the concept's meaning and the manner in which it is to be applied. At the very least, the approach suggested here is based on propositional units that have proved to carry some psychological reality (e.g., Kintsch, 1998) and measurement further took place in a meaningful context of analyzing authentic problems. When applying these convergence measures, future studies should provide detailed information on the conceptualization and measurement of that which forms the basis of convergence (i.e., their approach to measuring knowledge). (2) The measures suggested in this article are susceptible to blind spots in analyzing individual knowledge when learners choose not to share their thoughts, e.g. when learners build consensus quickly without further elaboration of what has been said. Knowledge may to a large extent be constructed on a social plane, but some learners may also choose not to participate in contributing ideas to discourse, instead learning from what they are told by their peers, teachers, or learning material. In assessing this "hidden" knowledge convergence, additional assessment techniques may be necessary, e.g. think-aloud protocols or interviews with individual students in order to investigate what kinds of ideas and thoughts they would not externalize in other tests. (3) The measures are susceptible to ambiguity of learners' contributions. For instance, learners may repeat contributions of their learning partners as a counter-argument, as a summary, or as something else. These ambiguities may be revealed by studying single cases of collaborative

learning. These studies may in turn serve to generate further hypotheses on more complex mechanisms of knowledge convergence, which in turn can be tested quantitatively in later stages of investigating knowledge convergence in collaborative learning, like, for example, collaborative completions (Barron, 2003; Roschelle & Teasley, 1993).

This article focused on the conceptualization of knowledge convergence phenomena and further suggested some measures applicable to these phenomena. We raised a number of red flags and indicated several limitations of knowledge convergence assessments in order to help future studies avoid some of the pitfalls associated with measuring knowledge convergence. We also discussed important limitations in measuring knowledge convergence and clarified at which points other approaches to the assessment of convergence and divergence in cognitive and social processes are more appropriate. Future studies in collaborative learning may apply the knowledge convergence measures along with other methods of assessment and thus accumulate further scientific knowledge on how learners acquire knowledge by mutually influencing each other in social interaction.

References

Aronson, E., Blaney, N., Stephan, G., Silkes, J., & Snapp, M. (1978). *The jigsaw classroom*. Beverly Hills, CA: Sage.

Barron, B. (2003). When smart groups fail. *The Journal of the Learning Sciences, 12*(3), 307-359.

Cannon-Bowers, J. A., & Salas, E. (2001). Reflections on shared cognition. *Journal of Organizational Behavior, 22*, 195-202.

Cohen, E. G. (1994). Restructuring the classroom: Conditions for productive small groups. *Review of Educational Research, 64*(1), 1-35.

De Lisi, R., & Goldbeck, S. L. (1999). Implication of Piagetian theory for peer learning. In A. M. O'Donnell & A. King (Eds.), *Cognitive perspectives on peer learning* (pp. 3-37). Mahwah, NJ: Erlbaum.

Fischer, F. (2001). *Gemeinsame Wissenskonstruktion. Analyse und Förderung in computerunterstützten Kooperationsszenarien [Collaborative knowledge construction. Analysis and facilitation in computer-supported collaborative scenarios]*. Unpublished professorial dissertation, Ludwig Maximilian University of Munich.

Fischer, F., & Mandl, H. (2005). Knowledge convergence in computer-supported collaborative learning: The role of external representation tools. *The Journal of the Learning Sciences, 14*(3), 405-441.

Ickes, W., & Gonzalez, R. (1996). "Social" cognition and social cognition. In J. L. Nyle & A. M. Brower (Eds.), *What´s social about social cognition? Research on socially shared cognition in small groups* (pp. 285-308). Thousand Oaks, CA: Sage.

Jeong, H., & Chi, M. T. H. (1999). *Constructing shared knowledge during collaboration and learning.* Paper presented at the AERA Annual Meeting, Montreal, Canada.

Kintsch, W. (1998). *Comprehension. A paradigm for cognition*. Cambridge: University Press.

Klimoski, R., & Mohammed, S. (1994). Team mental model: construct or metaphor. *Journal of Management, 20*(2), 403-437.

Roschelle, J. and S. D. Teasley (1995). The construction of shared knowledge in collaborative problem solving. In C.O`Malley (Ed.), *Computer supported collaborative learning*, (Vol. 128 pp.69-97). Berlin: Springer.

Roschelle, J. (1996). Learning by collaborating: Convergent conceptual change. In T. Koschmann (Ed.), *CSCL: Theory and practice of an emerging paradigm* (pp. 209-248). Mahwah, NJ: Erlbaum.

Teasley, S. (1997). Talking about reasoning: How important is the peer in peer collaboration? In L. B. Resnick, R. Säljö, C. Pontecorvo & B. Burge (Eds.), *Discourse, tools and reasoning: Essays on situated cognition* (pp. 361-384). Berlin: Springer.

Webb, N. M., Ender, P., & Lewis, S. (1986). Problem-solving strategies and group processes in small groups learning computer programming. *American Educational Research Journal, 23*(2), 243-261.

Weinberger, A., & Fischer, F. (2006). A framework to analyze argumentative knowledge construction in computer-supported collaborative learning. *Computers & Education, 46*, 71-95.

Weinberger, A., Ertl, B., Fischer, F., & Mandl, H. (2005). Epistemic and social scripts in computer-supported collaborative learning. *Instructional Science, 33*(1), 1-30.

Weiner, B. (1985). An attributional theory of achievement motivation and emotion. *Psychological Review, 92*, 548-573.

Table 1

Concepts of Weiner's attributional theory (1985) and information presented to the learners in the problem cases of the model study (see Appendix A)

Concepts of attribution theory			
		Locality	
		Internal	External
		Information of the problem cases (examples)	
Stability	Stable	Talent *The student: "I am simply not talented for maths"*	Task difficulty *Parents: "Maybe the test was too difficult"*
	Instable	Effort *The teacher: "Michael should work harder in maths"*	Chance *Peers: "You might be more lucky next time"*

Table 2

Two groups of three learners, each of which is able to construct a different set of adequate relations between concepts of a given theory and case information

	Group A			**Group B**		
Concept-case relations	*Leo*	*Lawrence*	*Lara*	*Tina*	*Thomas*	*Tim*
(1a) Talent = Stable attribution	x	-	-	x	x	x
(1b) Talent = Internal attribution	x	-	-	x	-	x
(2a) Effort = Instable attribution	-	x	-	x	x	-
(2b) Effort = Internal attribution	-	x	-	-	-	-
(3a) Task Difficulty = Instable attribution	-	-	x	-	-	-
(3b) Task Difficulty = External attribution	-	-	x	-	-	-

Table 3

Knowledge convergence processes and outcomes

		Real control groups	*Real groups with social script*	*Nominal control groups*	*Nominal groups with social script*
*Knowledge contributions equivalence**	*M*	*.06*	*.16*	*.06*	*.13*
	SD	*.03*	*.07*	*.05*	*.07*
Knowledge sharing[#]	*M*	*2.27*	*1.11*	*.68*	*.37*
	SD	*.40*	*.81*	*.26*	*.37*
*Outcome knowledge equivalence**	*M*	*.26*	*.19*	*.15*	*.14*
	SD	*.12*	*.06*	*.12*	*.08*
Shared outcome knowledge[#]	*M*	*.78*	*1.34*	*.46*	*.52*
	SD	*1.00*	*.56*	*.43*	*.29*

* Note: low values indicate knowledge equivalence

[#] Higher values indicate more shared knowledge

Table A1

Coding abbreviations for discourse activities and their frequency in the given discourse example

Coding Dimensions	*Coding Abbreviations*	*Lena*	*Anna*
Concept-Case Relations	*ACCR* = Adequate Concept-Case Relation	17	3
	IaCCR = Inadequate Concept-Case Relation	-	2
	CPS = Construction of Problem Space	1	-
	CCS = Construction of Conceptual Space	-	-
Social Mode of Co-Construction	*Ext* = Externalization	11	-
	Eli = Elicitation	-	1
	QCB = Quick Consensus Building	-	-
	IoCB = Integration-oriented Consensus Building	3	2
	CoCB = Conflict-oriented Consensus Building	4	2
Other	*Prompt* = Prompt that was part of the given computer-supported script	1	5

Appendix A

Example of a problem case

You participate in a school counselling as a student teacher of a high school with Michael Peters, a pupil in the 10th grade, who says:

"Somehow I begin to realize that math is not my kind of thing. Last year I almost failed math. Ms Weber, who is my math teacher, told me that I really had to make an effort if I wanted to pass 10th grade. Actually, my parents stayed pretty calm when I told them. Well, mom said that none of us is 'witty' in math. My father just grinned. Then he told that story when he just barely made his final math exams with lots of copying and cheat slips. 'The Peters family,' Daddy said then, 'has always meant horror to any math teacher.' Slightly cockeyed at a school party, I once have told this story to Ms Weber. She said that this was no bad excuse, but no good one either. Just an excuse that is, and you could come up with some more to justify to be bone idle. Last year I have barely made it, but I am really anxious about the new school year!"

Appendix B

Example of analysis of a scripted discourse excerpt

For the illustration of how knowledge is shared in asynchronous CSCL, consider the following example of a scripted discussion on the problem case outlined in Appendix A and examine how it is coded (see Weinberger & Fischer, 2006 for coding rules). Separators (|) indicate the segmentation. In cases in which learners have combined two dimensions, e.g. internal stable, two separate segments are counted. Square brackets with three dots ([…]) indicate an omission of text in this reproduction. Within the curly brackets, the concept-case relation and the social mode of co-construction is indicated (see table A1 for a glossary of abbreviations and the overall outcomes of the discourse examples presented below). Note that the original discussion was in German. The first message is sent by Lena at 10:12 am, enacting the role of case analyst.

| Michael attributes his bad performances to a lack of talent. {*ACCR* / *Ext*} | (internal {*ACCR* / *Ext*}| stable) {*ACCR* / *Ext*}| Mrs. W attributes his bad performances to a lack of effort {*ACCR* / *Ext*} | (internal {*ACCR* / *Ext*}| variable {*ACCR* / *Ext*}) and tries to motivate him anew {*ACCR* / *Ext*}| Michael's parents attribute his bad performances to a lack of talent, as he does. {*ACCR* / *Ext*}| […] | The consequences of the attributions of M. himself {*ACCR* / *Ext*}| and his parents have insofar rather unfavourable effects on Michael's learning behaviour and his motivation {*ACCR* / *Ext*}| whereas the external attribution of his math teacher has rather positive effects. {*ACCR* / *Ext*}|

With respect to the social mode of co-construction, this initial message of the discussion does not refer to any earlier messages. All propositional units can thus be regarded as externalizations. Lena contributes several adequate concept-case relations, e.g., lack of talent = internal attribution and lack of talent = stable attribution. She also contributed

adequate concept-case relations with respect to the attribution patterns of Michael's teacher and his parents.

Playing the role of a constructive critic and in response to the critic's prompts, written in capital letters, Anna replies to Lena's first message at 10:29.

| THESE ASPECTS OF YOUR ANALYSIS ARE NOT CLEAR TO ME YET: {*prompt*}|
Does not the fact, that M. thinks, he was untalented in math anyway, have negative effects on his effort? {*ACCR* / *Eli*}| […]|
WE HAVE NOT REACHED CONSENSUS CONCERNING THESE ASPECTS: {*prompt*}|
The teacher also does not really have a motivating effect on Michael, because she tells him to work harder {*IaCCR* / *CoCB*}|
MY PROPOSAL FOR AN ADJUSTMENT OF THE ANALYSIS IS: {*prompt*}|
She needed to get across to him that he is not completely untalented in math only because it seems to be a family tradition. {*IaCCR* / *CoCB*}| […]

Anna plays her role as a constructive critic as was intended by the script, first posing a question, then engaging in conflict-oriented consensus building and offering alternative analyses of the case. Although the propositional units including "motivation" is negatively related to "tell Michael to work harder" are not adequate from the perspective of Weiner's attribution theory (1985), she nevertheless contributes new ideas by saying that attribution patterns can be modified by training. Anna does not contribute as much target knowledge as Lena (knowledge contribution equivalence) and does not share knowledge in terms of integrating Lena's perspectives into her own, but continues discourse in a highly transactive way.

Lena replies to Anna's critique at 10:45 using the prompts that support the role of the case analyst.

| […] | REGARDING OUR DIFFERENCES OF OPINION: {*prompt*}|

Thinking that he is not talented {*ACCR* / *IoCB*}| has negative effects on his motivation, {*ACCR* / *IoCB*}| because the lack of talent (stable factor) means that all effort is in vain no matter how hard he tries. {*ACCR* / *IoCB*}| […] | The teacher attributes his failures to a variable cause, {*ACCR* / *CoCB*}| which means that he is talented in her opinion and could improve by increasing effort. {*ACCR* / *CoCB*}| She does not give up on him but motivates him in my opinion. {*ACCR* / *CoCB*}| She also says that lack of talent within the family is a mere excuse. {*CPS* / *CoCB*}| […]|

With respect to the social modes of co-construction, Lena replies to Anna's contribution by partly taking on her critique (*IoCB*), and partly responding in a conflict-oriented manner (*CoCB*). She further expresses knowledge and gives reasons why Michael's attribution pattern impedes his motivation to learn.

At 11:00 am, Anna sent this message:

| THESE ASPECTS ARE NOT CLEAR TO ME YET: {*prompt*}|
Ok, I understood now about motivation and talent. Thank you :-) {*ACCR* / *IoCB* }| […] |
WE HAVE NOT REACHED CONSENSUS CONCERNING THESE ASPECTS: {*prompt*}|
You are right in saying that his teacher does motivate him by not believing in the math-weakness of his family – otherwise he probably would not have passed math. {*ACCR* / *IoCB*}| […] |

In this last message of the discussion thread, Anna does not contribute any more new knowledge to the discussion, but accepts Lena's elaborations. Anna engages in integration-oriented consensus building and also constructs a relation between "motivation" and "not believing in the math-weakness of his family".

Overall, Lena and Anna do not show high values in knowledge contribution equivalence, since Lena constructs more adequate concept-case relations in her role as a case analyst than Anna in her role as a constructive critic. Lena and Anna finally share some knowledge with respect to the relationship between motivation and not attributing to a lack of

talent inherited within the family Anna deviates from her role as a constructive critic in her final message and engages in integration-oriented consensus building, which indicates that Anna has adopted some ideas from Lena.