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Knowledge Convergence in Collaborative Learning:

Concepts, Assessment, and a Model Study

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Abstract

In computer-supported collaborative learning (CSCL) the question has been raised regarding how locally distant learners influence each other and converge or diverge with respect to knowledge. This article provides measures that can be used for multiple concepts of knowledge convergence prior to, during, and subsequent to collaborative learning. Using a model study with 48 participants in 16 groups of three, we work to apply these measures and investigate how a computer-supported collaboration script can facilitate specific knowledge divergence processes and knowledge convergence outcomes. The results provide evidence for the reliability and validity of the knowledge convergence measures and show how a script may facilitate divergence processes and knowledge convergence outcomes in CSCL.

Keywords

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

Knowledge Convergence in Collaborative Learning: Concepts, Assessment, and a Model Study

Various collaborative learning approaches have been based on the idea that learners influence each other when learning together (e.g., De Lisi & Goldbeck, 1999; Roschelle, 1996). One important aspect of this mutual influence is that collaborative learners share knowledge through social interaction (Barron, 2003). As a consequence of this interaction, learners knowledge converges (Roschelle, 1996; Ickes & Gonzales, 1996). Knowledge convergence has been conceptualized as a group-level phenomenon describing how two or more individuals are similar or are becoming similar with respect to their knowledge (Fischer & Mandl, 2005).

In research on collaborative learning to date, many studies focus on individual level phenomena without considering knowledge convergence. This has been argued to be at least partly due to a lack of knowledge on how to conceptualize and measure group level phenomena (Jeong & Chi, 1999). However, the relevance of analyzing the knowledge convergence of learners in small groups has recently been recognized in computer-supported collaborative learning (CSCL). In CSCL environments, spatially distant learners construct knowledge together using computer applications (Fischer & Mandl, 2005). While computer-mediated communication may pose barriers for knowledge convergence processes and outcomes (Bromme, Hesse, & Spada, 2005), computer support may also guide distance learners to construct knowledge together, e.g., by scripting their interaction (Fischer, Mandl, Haake, & Kollar, in press).

In this article, we will suggest concepts and methods for analyzing knowledge convergence for small groups of learners. Then, by applying these concepts and methods to a model study, we aim to provide evidence for their reliability and validity, as well as their sensitivity with respect to instructional interventions. In this article, we will first conceptualize the phenomena of knowledge convergence at different stages of collaborative learning. Second, we will introduce the corresponding knowledge convergence measures. Third, we will present the results of a model study on how these measures could be used to more appropriately asses the effects of instructional support in computer-supported collaborative learning.

1. Conceptualizing knowledge convergence in collaborative learning

Knowledge convergence phenomena play an important role in collaborative learning prior to, during, and subsequent to the social interaction of collaborative learners. In the following paragraphs, we will provide different conceptualizations of knowledge convergence at the different stages of collaborative learning. In addition, we will also provide conceptualizations of knowledge divergence, which means that individuals within a group are or are becoming more dissimilar with respect to their knowledge.

1.1 Prior knowledge and its distribution among group members

Prior knowledge and its distribution are amongst the most important conditions of learning in small groups, due to the fact that subsequent processes and outcomes of collaboration depend strongly on them (see Fischer, 2001). Knowledge convergence prior to collaborative learning can be conceptualized in at least two different, but complementary ways. Learners may possess *shared prior knowledge*, which refers to the number of knowledge concepts the learners within one group have in common. Learners may also possess different learning resources and unshared prior knowledge, i.e. knowledge that their learning partner does not possess. For instance, in jigsaw scenarios of collaborative learning, (Aronson, Blaney, Stephan, Silkes, & Snapp, 1978) learning partners with complementary knowledge have to share their knowledge in order to collaboratively solve a learning task. *Prior knowledge equivalence* means that the learners in a group have similar amounts of knowledge prior to collaborative learning regardless of which concepts they know. Collaborative learning is often based on the idea that learners with different knowledge resources, but similar prerequisites, as for instance prior knowledge equivalence, construct knowledge together. According to a socio-cognitive conflict model of collaborative learning, for instance, learners would need a relatively equal quantity of prior knowledge to engage in more equal interaction (Hatano & Inagaki, 1991). At the same time, however, learners must have some areas of *un*shared prior knowledge in order to engage in and resolve socio-cognitive conflicts and thus construct knowledge together (De Lisi & Goldbeck, 1999). A study by Fischer (2001) showed that dyads with a dissimilar quantity of prior knowledge (i.e. one learner knows more than the other) acquire more knowledge in unstructured discussions than prior knowledge convergent dyads. In order to form groups in which members possess unshared prior knowledge, Dillenbourg and Jermann (in press) used the computer-supported collaboration script ArgueGraph. In this script, the positions of individual learners regarding the specific theories to be learned are being assessed and pairs of learners with maximally dissimilar positions according to the SWISH-model (Split Where Interaction Should Happen) are being formed. Different from the ArgueGraph script, scripts may also assign different roles to learners regardless of prior knowledge convergence. It was shown that learners in knowledge convergent dyads could be substantially supported in their knowledge acquisition by a collaboration script that structured learner interaction through assigning the roles of explainer and listener (Fischer, 2001). However, the same collaboration script seemed to be obstructive for knowledge divergent dyads, who may have applied reasonable interaction patterns on their own. The script seemed to interfere with the spontaneously emerging interaction patterns, because it assigned the roles of explainer and listener without regard to the individual learning resources and their distribution within the dyads. Prior knowledge convergence may thus interact with specific instructional support methods, such as computer-supported collaboration scripts.

1.2 Knowledge convergence processes

Knowledge convergence can also be regarded as a *process* that takes place during collaborative learning. Knowledge convergence *during* collaborative learning can be conceptualized in different ways. One approach is based on the idea that learners may contribute similar amounts of knowledge in discourse (*knowledge contributions equivalence*). Another approach is based on the notion that learners may share knowledge concepts through discussion (*knowledge sharing*). Some tasks require learners to establish and maintain a shared focus with regard to the concepts they are discussing. Other tasks may require learners to share complementary knowledge through discourse. Knowledge sharing may also be based on specific social interactions that involve incorporating the perspective of the other learning partners.

Knowledge sharing indicates how learners may converge with regard to individual knowledge concepts. Knowledge sharing means that learners share a focus during discourse, e.g. one learning partner gives explanations and the other learning partners incorporate these explanations into their own line of argumentation. In contrast, a socio-cognitive conflict model of collaborative learning would suggest that knowledge is constructed when learners are confronted with knowledge divergent to their own (see De Lisi & Goldbeck, 1999). From this perspective, learners are supposed to share complementary knowledge concepts through discourse to benefit from learning together. *Knowledge contributions equivalence* means that learners converge during the processes of collaborative learning with respect to the amount of knowledge they contribute through discourse. Learners who contribute similar or dissimilar amounts of knowledge concepts in discourse may not necessarily talk about the same knowledge concepts. In the socio-cognitive conflict model, learners are assumed to be rather similar in the amount of knowledge they contribute to a discussion (knowledge contributions equivalence), but diverge with regard to what they actually contribute (knowledge sharing).

1.3 Knowledge convergence outcomes

Knowledge convergence may also be considered an *outcome* of learning in small groups. Different approaches to collaborative learning highlight the idea that collaborative learners mutually influence the learning outcomes of their partners. Knowledge convergence outcomes can be regarded as evidence of this mutual influence. However, to date, only few studies have systematically considered knowledge convergence outcomes. Collaborative learning may aim to facilitate different types of knowledge convergence outcomes. On one hand, collaborative learners may expand their *shared outcome knowledge*, i.e. learners in one group have specific knowledge concepts in common. On the other hand, collaborative learning could facilitate the *outcome knowledge equivalence* of learners, i.e. two or more learners acquire similar amounts of knowledge. The few quantitative studies in the field to date show that collaborative learners share a surprisingly low percentage (< 20 %) of the theoretical maximum amount of knowledge they could potentially share after learning together (Fischer & Mandl, 2005; Jeong & Chi, 1999). In the study by Fischer and Mandl (2005), students of educational science collaborated in dyads in different conditions (via videoconferencing vs. face-to-face). Students then used different graphical representation tools (content-specific vs. content independent) to solve problem cases with specific theories in their domain. Neither the media condition nor the graphical representation tool influenced knowledge outcome convergence. Jeong and Chi (1999) found that the social interaction within dyads of college students, who were collaborating to learn a science text about the human circulatory system, was positively related to knowledge outcome convergence.

2. Knowledge convergence measurement

In the preceding section, we described different aspects of knowledge convergence. In this section we address how these may be measured. A number of approaches to collaborative learning consider knowledge convergence, but few of these approaches include the quantification of knowledge convergence as part of the associated empirical studies. In order to provide ways to empirically assess knowledge convergence, we will present methods for measuring different types of knowledge convergence prior to, during, and subsequent to collaborative learning.

2.1 Assessing prior knowledge equivalence

Prior knowledge equivalence means that two or more learners possess similar amounts of knowledge, but do not necessarily know the same concepts prior to learning together. In general, measures of dispersion can be used to analyze the differences in the amounts of knowledge between learners (see Ickes & Gonzales, 1996). However, most of the measures used, such as the standard deviation, are dependent on the means of the values they are derived from. The *coefficient of variation*, in contrast, 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 by the group mean. The coefficient of variation has mainly been applied in socio-economic studies on the equality of resources in societies (Allison, 1978). We would suggest the following procedure for assessing prior knowledge equivalence. First, the individual prior knowledge scores must be calculated. These form the basis for measuring prior knowledge equivalence. Second, the standard deviations of the mean knowledge scores of learners within one group are aggregated. This is done because this measure for dispersion indicates the extent to which learners deviate and are thus dissimilar from the group mean. In order to express prior knowledge equivalence, we suggest multiplying the aggregated standard deviations by -1 and then z-standardizing. However, if you make repeated measurements, z-standardizing leads to equal means at each measurement. In this case, prior knowledge equivalence should not be z-standardized, because no within-subject effect could be examined.

A problem with the prior knowledge equivalence measure is that it does not provide information about the absolute amount of similar knowledge learners have. This is because concepts that are not known by any of the group members contribute to these convergence scores. In this way, high prior knowledge equivalence scores may indicate both knowledge convergence as well as "ignorance convergence". Ignorance convergence means that learners are equally unable to respond correctly to single knowledge items. To differentiate between knowledge and ignorance convergence, the expected and the observed individual knowledge scores can be compared. If the observed scores are higher than the expected scores, prior knowledge equivalence is based on known rather than unknown knowledge elements. Similarly, observed scores that are lower than the expected scores indicate the opposite.

2.2 Assessing shared prior knowledge

To measure shared prior knowledge, we would suggest using a measure, which is based on pair-wise comparisons of knowledge items that learners can adequately respond to prior to collaborative learning. In contrast to the measure of prior knowledge equivalence, this measure only indicates knowledge convergence and not ignorance convergence. In order to compare the knowledge of one learner with the knowledge of another learner, the individual items that learners know need to first be assessed in a test. Second, the pair-wise comparisons are conducted by comparing all possible pairs within small groups to determine if the learners share an individual knowledge concept, i.e. are able to respond to one and the same knowledge item in the same way. Third, in order to evaluate the individual comparisons, a value of one is assigned to any pair within the small groups that shares a single knowledge concept. Fourth, the shared prior knowledge score is calculated by the sum of all these values within each small group. Since the measure for shared prior knowledge is based on the individual scores and due to the fact that individual learners may possess extremely 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 weighted differently. 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 equaling 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, a shared prior knowledge value of zero is assigned.

2.3 Assessing knowledge contributions equivalence during collaboration

Equivalent knowledge contribution means that two or more learners contribute similar amounts of knowledge to the discourse, but do not necessarily share a joint focus of the discussion. In order to measure knowledge contributions equivalence, the knowledge explicated through the learner's discourse needs to be identified. Therefore, the first step in analyzing knowledge contributions equivalence is to segment the discourse corpora and code the discourse for the individual knowledge concepts externalized by the learners. The coding of the discourse corpora needs to be based on a set of rules and tested for inter-rater reliability. The learners' use of theoretical concepts in discourse can be regarded as an indicator for knowledge during the processes of collaborative learning, (Weinberger & Fischer, in press). Once the knowledge processed by the individual learners during collaborative learning has been assessed, the procedure to measure knowledge contributions equivalence is the same as the procedure to measure prior knowledge equivalence. In other words, coefficient of variation is calculated based on the knowledge concepts that learners process during collaborative learning. Similar to the measure for prior knowledge equivalence, the measure for knowledge contributions equivalence does not indicate if the knowledge contributions equivalence is based on knowledge or ignorance. Therefore, the expected and observed total number of the knowledge concepts contributed by the individual learners during collaborative learning must be compared simultaneously to identify if the equivalent knowledge contribution score is based on known or unknown knowledge elements.

2.4 Assessing knowledge sharing during collaboration

Knowledge sharing means that two or more learners discuss the same or complementary knowledge concepts during collaborative learning. As in the method for measuring knowledge contributions equivalence, the individual knowledge concepts that learners contribute in discourse must be identified. After that, the measure for knowledge sharing is built analogously to the measure for shared prior knowledge and is based on pair-wise comparisons of learners who have discussed the same knowledge concepts during collaborative learning. For each of the small groups of learners, we evaluate whether each possible pair has contributed the same knowledge concept in discourse. If learners within those pairs have contributed the same knowledge concept, a value of one for knowledge sharing is assigned to the small group of learners. If all learners within one group have contributed the same knowledge concept in discourse, the total value equals the number of members of the small group. Finally, the score is normalized by dividing by the mean value of the small group.

2.5 Assessing outcome knowledge equivalence

Outcome knowledge equivalence means that two or more learners have acquired similar amounts of knowledge subsequent to and as a consequence of learning together. The coefficient of variation can be calculated for each small group of learners and aggregated to build the measure of outcome knowledge equivalence based on individual knowledge items that learners can or cannot adequately respond to in post-tests on knowledge. This measure is thus built analogously to the measures for prior knowledge equivalence and knowledge contributions equivalence, but is based on the individual scores from post-tests on knowledge.

One difficulty in measuring outcome knowledge equivalence is identifying the extent to which knowledge convergence outcomes can be traced back to the actual mutual influence during social interaction within the learning groups rather than to other factors, such as chance. In the following paragraphs, we present approaches to deal with causes of knowledge convergence other than social interaction, namely (1) *extremely high or low individual knowledge scores*, (2) *chance* or (3) being provided with the *same learning resources* and being exposed to the *same learning environment*. In order to investigate specific theoretical assumptions on knowledge convergence, we need to ensure that knowledge convergence is an effect of the social interaction of learners and exclude alternative explanations.

(1) If the measure for knowledge outcome convergence is based on extremely low or extremely high individual knowledge scores, assertions on knowledge convergence cannot be traced back to mutual influence in social interaction during collaborative learning, but may be an *artefact of the transformation of the individual knowledge scores*. For instance, if learners have acquired all knowledge that enters the knowledge convergence measures, learners would artificially also attain perfect knowledge convergence. This is because the perfect knowledge scores would have no dispersion within the small groups of learners. Therefore, a pre-condition for assessing this value is that the difficulty of the knowledge items vary closely around the optimal value of $p = .50$. This medium item difficulty means that about half of the learners are able to respond to the item correctly, which excludes floor- or ceiling effects on the scores. Therefore, medium item difficulty affirms that knowledge convergence is not based on extreme values of the individual knowledge measures. If the condition of medium item difficulty is not met, a post hoc solution to this problem is to only use the middle quartiles of the sample to test knowledge convergence. This approach can be expected to prevent floor- or ceiling effects. However, this approach also halves the size of samples and therefore the statistical power.

(2) Learners may also attain outcome knowledge equivalence due to *chance* rather than social interaction during collaborative learning. Therefore, another approach to certify that knowledge convergence can be traced back to social interaction is to control for the coincidental co-occurrence of knowledge of two learners or more. In order to adequately address the fact that knowledge convergence may not be a result of social interaction, but chance concurrence, measures that are adjusted for chance concurrence may need to be applied, e.g., Fleiss' Kappa (Fleiss, 1971).

(3) Another cause of knowledge outcome convergence other than the social interaction during collaborative learning is that the *learners experience the same learning environment* as their learning partners. Learners may converge, for instance, because they have been

confronted with identical learning material rather than due to social interaction with their learning partners. One approach to addressing this problem (as well as chance convergence) is based on 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 not with each other. This approach has been applied in studies on knowledge convergence in collaborative learning (Fischer & Mandl, 2005; Jeong & Chi, 1999). The comparison of real and nominal groups helps to identify knowledge convergence that results from social interaction in real groups as opposed to knowledge convergence that results from learning and collaborating under the same conditions and having access to the same learning materials.

2.6 Assessing shared outcome knowledge

Shared outcome knowledge means that two or more learners have acquired knowledge on the same concepts as a consequence of learning together and are thus able to respond to the same items in a knowledge test subsequent to collaborative learning. The measure for shared outcome knowledge is similar to the measures for shared prior knowledge and knowledge sharing. This measure is based on comparing pairs of learners with respect to the adequacy of their responses to individual items in a knowledge test. As was the case with outcome knowledge equivalence, shared outcome knowledge needs to be controlled for influences other than the social interaction of learners during collaborative learning. A pre-requisite for measuring shared outcome knowledge is therefore medium item difficulty. If this condition is not met, the same post-hoc solutions as is used with outcome knowledge equivalence can be applied. To recap, these solutions are to compare real groups with nominal groups, to control for chance concurrence using Fleiss' Kappa (Fleiss, 1971) or to use only the middle quartiles of the sample. Another post hoc approach to investigating the extent to which shared outcome knowledge is based on social interaction during collaborative learning is to normalize the shared outcome knowledge scores using the means of the small groups. For example, this would mean that the shared outcome knowledge scores of each small group are divided by the mean of the same group's score on the individual knowledge test. As with using the middle quartiles only, there are, however, costs associated with this normalization. Although this procedure may exclude the artificial effects of the absolute individual values, it does so at the cost of reducing explanatory power by reducing the variance of the knowledge convergence measures. Thus, it is more likely that actual effects and differences regarding knowledge convergence may not be found with normalized measures, as opposed to if non-normalized measures for shared outcome knowledge are used.

3. Model study of knowledge convergence

In order to illustrate how the different approaches to measure knowledge convergence can help assess the effects of instructional support and to better understand the processes and outcomes of CSCL, we will present a study on how instructional support provided through computer-supported collaboration scripts can influence knowledge convergence. This study is based on the re-analysis of data that had previously been analyzed with a focus on individual level phenomena (see Weinberger et al., 2005, for a detailed description). Furthermore, the study aims to cross-validate the different concepts for knowledge convergence at the different stages of collaborative learning.

In this study, we investigated the effects of a script on knowledge convergence processes and outcomes of distance learners in small groups of three. The learners, who were students of Educational Science, were to analyze and discuss three problem cases with the help of Weiner's attribution theory (1985). The task was carried out in small groups communicating via web-based discussion boards. The goal was to learn to apply this theory. We analyzed the knowledge concepts that the learners contributed in the discussions as well as the knowledge concepts that learners used in an individual post-test consisting of different problem cases. The social script that was used aimed to facilitate divergence processes and convergence outcomes between peers by structuring their social interaction in accordance with the socio-cognitive conflict model of collaborative learning. The social script provided the roles of case analyst and constructive critic, supported these roles with specific prompts that were automatically inserted into the text windows of the learners, and provided learners with a specific sequence for performing these roles. The case analyst first composed an initial analysis of the problem case. Then the two critics contributed critiques to which the case analyst could reply. After another round of critiques, the case analyst had to write a final analysis based on the preceding discussion. In this study, this social script was proven to facilitate the individual acquisition of multi-perspective application-oriented knowledge. Through this re-analysis we aim to investigate whether the social script had an effect on knowledge convergence processes and outcomes.

In addition to analyzing the influence of a social script on knowledge convergence processes and outcomes, we will compare the real groups of three with nominal groups. This comparison will help to investigate the influence of social interaction on knowledge convergence processes and outcomes in contrast to influences caused by the same learning environment. Learners who have actually collaborated are compared to random nominal groups, which consist of participants who experienced the same collaborative learning environment, but who have collaborated with other participants. Based on collaborative learning approaches, it could be expected that learners in real groups will have higher scores for knowledge convergence than learners in nominal groups. Furthermore, we will control for prior knowledge convergence of the learners with regard to prior knowledge equivalence as well as shared prior knowledge. Using a two-way ANOVA we varied the between-subject factor “social script” (with vs. without) and independently compared real with 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.

The research questions of the study are as follows:

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

Expectations regarding RQ 1 are that the social script would facilitate knowledge divergence processes compared to an unstructured collaboration condition. Learners supported by the social script are expected to contribute different amounts of knowledge regarding one problem case due to their different roles (*knowledge sharing*) and are also expected to contribute complementary knowledge concepts (*knowledge contributions equivalence*).

The real groups are expected to score higher in knowledge sharing than the nominal groups, because real groups may have a shared focus on specific knowledge concepts during collaborative learning. Differences between real and nominal groups regarding knowledge contributions equivalence can be expected in either direction. This is due to the fact that learners may either adapt to the social norm of the real group by contributing knowledge equally or certain learners within real groups may contribute more knowledge concepts than others. Learning partners may also adapt by reducing contribution of knowledge concepts themselves.

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

The expectations regarding RQ 2 are that learners supported with the script will achieve higher scores for equivalent and shared outcome knowledge than learners without a script. Scripted learners are expected to converge towards shared knowledge, because they are guided in resolving socio-cognitive conflicts. Since the script guides learners to participate more equally over all three problem cases, it should help learners to benefit more equally from collaborative learning than learners without the script.

It can be further hypothesized that real groups will attain more shared outcome knowledge due to their social interaction than nominal groups. For outcome knowledge equivalence, learners may either have converged towards a social norm or may benefit differently from social interaction within the real groups.

3.1 Sample and design of the model study

The sample consisted of 48 students of Educational Science at the University of Munich. The participants were randomly assigned to one of two experimental conditions in the two-factorial design study using the factors social script (with vs. without). Post hoc, a comparison between real and nominal groups was performed by randomly assigning all participants to nominal groups. The procedure of the study included (1) an introduction to the learning environment and pre-tests, (2) an individual learning phase, in which learners studied a three-page description of a psychological theory (attribution theory of Weiner, 1985), and (3) a collaborative phase of 80 minutes, in which learners analyzed and discussed problem cases based on Weiner's attribution theory, e.g., problem cases of students that suffer from dysfunctional attribution patterns. (4) Finally, the individual participants analyzed a transfer problem case in a post-test.

3.2 Prior knowledge convergence in the model study

In order to warrant that the individual knowledge values were independent from the knowledge convergence measures, test items of medium difficulty were selected. However, in the pre-test about ¾ of the participants did not score. Due to this floor effect, prior knowledge could not be measured reliably. Without reliable prior knowledge measures, the respective knowledge convergence measures also could not be reliably assessed. Thus, in this case, the value of prior knowledge equivalence was expected to be high due to shared ignorance. Learners would be highly similar regarding the amount of knowledge they would possess prior to collaborative learning, but this amount of knowledge would be extremely small. The ¾ of the learners who did not score at all would have perfectly prior knowledge equivalence due to having no prior knowledge at all. The learners who knew or did not know to respond correctly were equally distributed over all four conditions ($\chi^2_{(3)} = .00 - .29$, *n. s.*).

Both measures for knowledge convergence processes, *knowledge sharing* and *knowledge contributions equivalence*, are based on the individual knowledge concepts that each of the learners contribute in discourse. Therefore, to analyze knowledge sharing and knowledge contributions equivalence, the written discussions of the learners for one of the three problem cases were segmented. This segmentation was based on epistemic units that consisted of relations between theoretical concepts and case information (87% rater agreement). The segments were analyzed with regard to the knowledge concepts that learners applied during collaborative learning. The empirical maximum of the number of different knowledge concepts learners applied during collaborative learning was 7. The item difficulty of applying the single knowledge concepts during collaborative learning ranged from p_{min} = .44 to p_{max} = .79. The knowledge scale during collaborative learning was coded reliably (Cohen's κ = .90) and was consistent (Cronbach's α = .83). Similarly, the measures of knowledge convergence outcomes, *shared outcome knowledge* and *outcome knowledge equivalence*, are based on the individual items of a post hoc knowledge test. The knowledge scale of the post-test was based on 5 items of medium difficulty (p_{min} = .27; p_{max} = .40) and was sufficiently reliable (α = .70). The data were segmented and coded with respect to the specific concepts that learners were able to apply adequately. This means that the individual knowledge underlying the knowledge convergence measures was reliably assessed. Furthermore, the individual items constituting the knowledge scales in the model study were of medium difficulty, which means that the knowledge convergence measures were largely independent of the individual knowledge scores.

4. Results of the Model Study: Application of the Knowledge Convergence Measures

4.1 Knowledge contributions equivalence

It was expected that learners who used the script would contribute different amounts of knowledge during collaboration due to their different roles within one problem case. The analysis shows that groups supported with the social script had lower *knowledge contributions equivalence* scores (see table 1). As expected, scripted learners contributed less similar amounts of knowledge concepts in the discussions than unscripted learners, i.e. the script reduced knowledge contributions 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 in real groups, it was expected that learners would adjust the amount of knowledge they contributed through social interaction during collaborative learning. However, *knowledge contributions equivalence* could not be traced back to the social interaction within real groups $F(1,14) = 0.39$; *n. s,* i.e. there was no effect and the real groups did not differ from nominal groups with respect to knowledge contributions equivalence. These results confirm the hypothesis about the influence of the social script, but do not indicate whether social interaction encourages or impedes knowledge contributions equivalence. It is possible that the different influences of social interaction on similar or dissimilar amounts of knowledge contributions cancelled each other out.

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Insert table 1 about here

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4.2 Knowledge sharing

The knowledge sharing measure indicates the extent to which learners contributed the same knowledge concepts during collaborative learning. Within the real groups in all conditions, 50 % of the knowledge items were unshared, 30 % were partly shared, i.e. shared between two members only within the groups of three, and 20 % of the knowledge items were shared by all three members. With respect to knowledge sharing, groups supported by the social script scored lower (see table 1), 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 scored higher in knowledge sharing than nominal groups, which was also found to be a significant and large effect, $F(1,14) = 47.63$; $p < .05$; $\eta^2 = .77$. This result strongly indicates that a large part of knowledge sharing can be traced back to the social interaction within the real groups and cannot be fully explained by learners working under the same experimental conditions.

4.3 Outcome knowledge equivalence

The script was expected to facilitate knowledge convergence outcomes. With respect to outcome knowledge equivalence (see table 1), no effect of the script could be found, $F(1,14) = 2.73$; *n. s*. The results further show a large effect at the 10% significance level indicating that the nominal groups had 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 do not benefit equally from collaborative learning. In contrast to our assumptions, the results indicate that the script did not affect outcome knowledge equivalence and that real groups attained lower outcome knowledge equivalence than nominal groups. This last result supports the notion that learners within small groups benefit from collaborative learning to substantially different degrees (e.g., Webb et al., 1986).

4.4 Shared Outcome Knowledge

Regarding shared outcome knowledge across all real groups, 50 % of the knowledge items were unshared, 34 % were partly shared, i.e. only shared between two members within the groups of three, and 16 % of the knowledge was shared by all three members of the real groups. With respect to shared outcome knowledge, groups supported by the social script scored higher (see table 1). This means that scripted learners converged more towards shared knowledge subsequent to learning together than learners without script. This was found to be a large effect, which is significant at the 10% level, $F(1,14) = 3.09$; $p = .10$; $\eta^2 = .18$. 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 social interaction in real groups facilitate shared outcome knowledge.

5. Discussion of the results of the model study

First, the model study served to validate the knowledge convergence measures by investigating if the measures would be sufficiently sensitive for assessing the effects of a social script designed to facilitate knowledge divergence processes and knowledge convergence outcomes. The model study shows that the effects on the different knowledge convergence processes can be assessed reliably. The study also revealed that the knowledge convergence measures are valid and sensitive to the script as well as to the comparison of real vs. nominal groups in the hypothesized direction. However, the knowledge convergence measures are based on individual knowledge scores and are thus not only dependent on these scores, but also dependent on each other. We therefore need to investigate these dependencies in order to identify further prerequisites and restrictions of these measures. Second, the model study aimed to investigate the effects of a social script on knowledge convergence in computer-supported collaborative learning. The results regarding the RQs investigated indicate that the social script could support knowledge divergence processes as intended, i.e. learners with the script contribute different amounts of knowledge and contribute complementary knowledge concepts to the discourse. Members of the small groups with the script were more dissimilar with regard to the amount of knowledge concepts they contributed to discourse (*knowledge contributions equivalence*). These groups were also more dissimilar with regard to the focus of their contributions (*knowledge sharing*). Furthermore, there are indications 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. However, the script did not affect *outcome knowledge equivalence*. Furthermore, knowledge sharing and shared outcome knowledge seems to be strongly connected to learning together in real groups, as compared to learning within the same learning environment. However, not all members of real groups benefit equally regarding the amount of knowledge that they acquire. For example, real groups had lower scores for outcome knowledge equivalence than nominal groups. This result indicates that members of small groups benefit less equally than expected because of the shared conditions of the learning environments. Therefore it can be concluded that, independent of their instructional support, discussions tend to lead to divergent quantities of outcome knowledge, but also result in more shared outcome knowledge.

In summary, the approach of encouraging divergence during the processes of collaborative learning to facilitate shared outcome knowledge seems to be feasible (e.g., Dillenbourg & Jermann, in press). Learners can obtain shared knowledge through (divergent) social interaction, as opposed to being provided with the same learning material. However, encouraging knowledge divergence processes does not seem to facilitate outcome knowledge equivalence. Some learners within groups still benefit more than others from collaborative learning (e.g., Webb et al., 1986). Overall, these results would suggest facilitating knowledge divergence processes with respect to shared outcome knowledge. However, in order to ensure that learners benefit more equally from collaborative learning, knowledge contributions equivalence may need to be encouraged instead of knowledge divergence processes.

6. 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). Measuring knowledge convergence prior to, during, and subsequent to collaborative learning helps us to investigate more specifically how learners influence each other, as opposed to only analyzing individual activities. Thus, we can expand our understanding of how individual roles and activities of collaborative learners need to be orchestrated within learning groups to facilitate knowledge construction. Applying the knowledge convergence measure in the model study showed how members of one and the same group benefited differently from collaborative learning. Such an understanding could not be gained by merely analyzing individual phenomena. The study showed how instructional support may not only influence individual learning, but also may influence the distribution of knowledge in small groups. Thus, instructional support for collaborative learning can be improved with regard to effects on knowledge convergence and its interaction with individual outcomes. Furthermore, collaborative learning may be aimed not only at supporting individual knowledge construction, but also knowledge convergence. Knowledge convergence measures need to be applied by default in research on CSCL cases where distance learners may need to be additionally supported to share knowledge. These measures should be used to evaluate theoretical assumptions and to consolidate findings of knowledge convergence in CSCL in studies with larger numbers of participants. First, group level analyses require more participants than individual level analyses, and knowledge convergence may not always be overtly visible and easy to survey. Therefore, more studies need to be conducted to increase the validity of the knowledge convergence measures. Second, the results of the few studies on knowledge convergence raise further questions regarding collaborative learning. These questions can be answered in further studies that apply the knowledge convergence measures introduced in this article. Thus, investigating knowledge convergence may encourage the development and refinement of theoretical assumptions regarding collaborative learning.

This article focused on conceptualizing knowledge convergence phenomena and suggested some applicable measures for these phenomena. We raised some red flags to help future studies avoid some of the pitfalls associated with measuring knowledge convergence. Future studies in collaborative learning may easily apply these knowledge convergence measures alongside individual measures to accumulate further knowledge on how learners acquire knowledge by mutually influencing each other through social interaction.

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References

Allison, P. D. (1978). Measures of inequality. *American Sociological Review*, *43*, 865-880.

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.

Bromme, R., Hesse, F. W. & Spada, H. (Eds.), (2005). *Barriers and biases in computer-mediated knowledge communication – and how they may be overcome*. New York : Springer.

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.

Dillenbourg, P. & Jerman, P. (in press). SWISH: A model for designing CSCL scripts. In F. Fischer, H, Mandl, J. Haake & I. Kollar (Eds.) *Scripting computer-supported communication of knowledge - cognitive, computational and educational perspectives*.

Fischer, F. (2001). *Gemeinsame Wissenskonstruktion. Analyse und Förderung in computerunterstützten Kooperationsszenarien [Collaborative knowledge construction. Analysis and facilitation in computer-supported collaborative scenarios].* Ludwig-Maximilians-Universität München, München.

Fischer, F., Mandl, H., Haake, J., & Kollar, I. (Eds.), (in press). *Scripting computer-supported communication of knowledge - cognitive, computational and educational perspectives*.

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.

Fleiss, J.L. (1971). Measuring nominal scale agreement among many raters. *Psychological Bulletin, 76*, 378-381.

Hatano, G., & Inagaki, K. (1991). Sharing cognition through collective comprehension activity. In L. Resnick, J. M. Levine & S. D. Teasley (Eds.), *Perspectives on socially shared cognition* (pp. 331-348). Washington D. C.: American Psychological Association.

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.

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

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.

Slavin, R. E. (1993). Synthesis of research on cooperative learning. In A. E. Woolfolk (Ed.), *Readings & cases in educational psychology* (pp. 170-178). Needham Heights: Allyn & Bacon.

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. (in press). A framework to analyze argumentative knowledge construction in computer-supported collaborative learning. *Computers & Education*.

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

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*

* negative values due to multiplication by -1 in order for higher values to indicate knowledge contributions equivalence and outcome knowledge equivalence respectively with the maximum = 0 for both variables