Developing Adaptive Collaboration Support: The Example of an Effective Training for Collaborative Inference

Originally published in:
Educational Psychology Review 22(1), https://doi.org/10.1007/s10648-010-9119-6

Developing adaptive collaboration support: the example of an effective training for collaborative inferences

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This is the authors' last version of the article published under https://doi.org/10.1007/s10648-010-9119-6

Please cite as:

Deiglmayr, A., & Spada, H. (2010). Developing adaptive collaboration support: the example of an effective training for collaborative inferences. *Educational Psychology Review, 22*(1), 103-113.

Abstract:

Adaptive support for computer-mediated collaboration aims at increasing learners' collaboration skills by providing support that is tailored to their actual needs, and by fostering their self-regulation. This review gives an example of developing support for a specific collaboration skill: the co-construction of genuinely new knowledge by drawing collaborative inferences. It shows how the development of increasingly detailed and accurate collaboration models and the implementation of an online assessment led towards the development of an effective training with adaptive tutoring support. In doing so, it outlines and illustrates a sequence of four steps in developing and testing adaptive collaboration support: deciding which collaboration skill(s) to support; conceptualizing the individual and collaborative activities underlying the skill; specifying rules for providing adaptive support based on an online assessment of collaboration indicators; and evaluating adaptive collaboration support.

Keywords: adaptive collaboration support; tutoring tools; knowledge co-construction; inferences

Collaborative learning and problem-solving in computer-mediated settings are becoming more and more important in our increasingly globalized and specialized society. However, students typically need training and assistance before they can engage in effective computer-mediated collaboration. Research in the field of computer-supported collaborative learning, in particular, has aimed to enhance the effectiveness of such support. Recently, the focus of this line of research has been moving from providing fixed to increasingly adaptive support (Carmien, Kollar, Fischer, & Fischer, 2007; Baghaei, Mitrovic, & Irwin, 2007; Gweon, Rosé, Zaiss, & Carey, 2006). One reason for this shift has been the insight that students enter collaboration already equipped with more or less specific assumptions about effective collaboration, and that "overscripting" students may disrupt self-regulated collaboration and reduce motivation (Dillenbourg & Jermann, 2007). Adaptive collaboration support is better tailored to students' actual needs (Park & Lee, 2004) and thus minimizes the risk of overscripting. In addition, while earlier studies used collaboration mainly as a vehicle for the acquisition of domain-specific knowledge, learning how to collaborate effectively is now considered a goal in itself (e.g. Carmien et al., 2007; Rummel & Spada, 2005). Adaptive support is designed to facilitate students' increasing self-regulation (VanLehn et al., 2005) and thus is typically seen as better suited for this goal than fixed support.

In analogy to the acquisition of *cognitive skills* that is the aim of adaptive instructional communication in individual problem-solving (VanLehn, 1996), the acquisition of *collaboration skills* can be conceptualized as the aim of adaptive collaboration support. Like cognitive skills, collaboration skills can be conceptualized as procedural, strategic knowledge that tells collaborators what actions to perform under which conditions (Taatgen, Huss & Anderson, 2008; VanLehn, 1996). Just as the design of adaptive instructional systems for cognitive skill acquisition requires detailed models of the cognitive activities underlying a

given skill, the design of adaptive support for collaboration skill acquisition also requires detailed models of the individual and collaborative activities underlying the targeted skill. In addition, giving adaptive support for both cognitive and collaboration skill acquisition necessitates a fine-grained, online analysis of the ongoing problem-solving processes, as well as rules for providing just-in-time feedback, hints and prompts based on that assessment. Thus, developing adaptive support also contributes to the designers' understanding of the skills they are trying to support.

In this short review, we give an example of developing adaptive support for a specific collaboration skill: the co-construction of genuinely new knowledge by drawing collaborative inferences. We show how the development of increasingly detailed and accurate collaboration models and the implementation of an online assessment and a set of tutoring rules led towards the development of an effective training with adaptive support. In doing so, we outline a sequence of steps in the design of adaptive collaboration support. In contrast to the emerging literature on intelligent collaboration tutoring systems whose designers aim to implement formal models of collaboration (e.g. Baghaei et al., 2007; Gweon et al., 2006; Soller, 2001), we focus on a set of minimal requirements. Specifically, we suggest the following steps: deciding which collaboration skill(s) to support; conceptualizing the individual and collaborative activities underlying the skill; specifying rules for providing adaptive support based on an online assessment of collaboration indicators; and evaluating adaptive collaboration support.

Deciding Which Collaboration Skills to Support

Collaboration skills do not only have cognitive but also social, emotional, and motivational aspects (cf. Rummel & Krämer, this issue). Thus, the goals of adaptive collaboration support can be defined along several dimensions (Meier, Spada, & Rummel, 2007): For example,

depending on the task and setting, it might be more important to help students communicate more effectively, improve their joint information processing, coordinate individual and collaborative efforts or the use of technical tools, maintain a productive and emotionally satisfying working relation, or uphold a high motivational involvement with their task (for an alternative classification see Soller, 2001). Another distinction can be made between support for cognitive and social skills on the one hand, and meta-cognitive and meta-social skills on the other hand (Diziol & Rummel, in press). Further, support measures will differ in scope: on one side of the continuum, support can be given on a global level, targeting collaboration and problem-solving skills at the same time (e.g. Rummel & Spada, 2005); on the other side, support can be provided for very specific activities, like the construction of well-designed arguments (Weinberger, Stegmann, Fischer, & Mandl, 2007). In our own research, we focus on a relatively specific, but very important collaboration skill: the drawing of collaborative inferences by which collaborators can co-construct new knowledge.

Example: Drawing Collaborative Inferences as an Important Collaboration Skill

Collaborative learning activities in which students build upon one another's contributions and actively co-construct ideas, explanations, and solutions have the potential to be more effective than even the most constructive individual learning activities (Chi, 2009). Similarly, merging insights from various fields of expertise and integrating diverse viewpoints enables groups to develop innovative solutions and make well-informed decisions (Stasser & Birchmeier, 2003). To reach such synergy effects, however, collaborators need to be able to co-construct new insights by integrating their complementary information resources. An important collaboration skill in this respect is the drawing of collaborative inferences: collaborative inferences integrate information that was initially distributed between collaboration partners (for details and examples, see Meier & Spada, in press). Thus, they allow for the collaborative construction of new knowledge that could not have been created by an individual problem-

solver alone, resulting in a true assembly bonus and a great learning opportunity. In our research we therefore focus on collaborative inference drawing as an important skill to analyze and support.

A Collaborative Inference-Drawing Task. In one of the problem-solving tasks we use, dyads of university students have to find the only guilty person among four suspects in a fictitious homicide investigation (Meier & Spada, in press). Students sit in separate rooms with PCs and communicate over an audio connection. The dyads' task is to make a joint decision for one of the suspects and provide a written justification in a shared text document. Participants first study a set of "interrogation protocols" individually, and then discuss the case with their partner who has received a systematically different set of information. To find the correct solution, students must create new knowledge by drawing inferences from pairs of interdependent text information. For example, they can draw a solution-relevant inference by combining the information that the murderer put the gun into the victim's right hand, even though the victim was in fact left-handed, with the information that one of the suspects knew the victim was left-handed.

Three Types of Inferences. The relevance of collaborative inferences for making use of complementary knowledge resources is most apparent in their comparison with two other types of inferences that do not require collaborative information processing. *Collaborative inferences* result from information that is unshared (i.e. information that is known by only one person), and is distributed between collaborators. Thus, an inference of this type can only be drawn by both partners collaboratively, resulting in genuinely new shared knowledge. *Individual inferences* also result from unshared information, which is, however, located with the same person. An inference of this type can therefore be drawn individually by that person, without the need for collaboration. *Shared inferences*, finally, result from shared information

that is known to both partners. An inference of this type can be drawn individually by any of the partners, or collaboratively between them. In the murder-mystery task, the available information is distributed in such a way that a third of the solution-relevant inferences are collaborative, a third are individual, and a third are shared, allowing for systematic comparisons between the three inference types.

Collaborative < Individual < Shared Inferences. Across our studies, we find that, at least in unsupported collaboration, shared inferences are the most likely and collaborative inferences the least likely to be actually drawn during group discussions (Meier & Spada, 2008, in press, submitted). Similar results were also obtained by Härder (2003). More generally, these findings connect to a large body of social-psychological literature on information pooling in groups showing that groups tend to focus on shared information and neglect unshared information during collaborative decision-making (for a recent review, see Brodbeck, Kerschreiter, Mojzisch, & Schulz-Hardt, 2007); though this research focuses on information pooling rather than knowledge co-construction. Thus, in summary, the exchange of unshared information in general and the successful drawing of collaborative inferences in particular seem to constitute relatively rare moments of particularly fruitful collaboration, and, thus, an important collaboration skill to support.

Conceptualizing Individual and Collaborative Activities Underlying the Targeted Skill

Support for cognitive skill acquisition in a given domain is typically based on an analysis of the cognitive activities that are necessary for successful problem-solving, e.g. the application of specific rules or concepts (Anderson, Corbett, Koedinger, & Pelletier, 1995; VanLehn, 1996). Similarly, support for the acquisition of collaboration skills is typically informed by an analysis of the specific individual and collaborative activities underlying those skills. In line with previous authors, we distinguish between collaboration structuring and collaboration

regulation approaches (Soller, Martinez, Jermann, & Muehlenbrock, 2005). In *collaboration structuring* approaches (also called design-based scaffolding by Zumbach, Reimann, & Koch, 2006) all groups receive the same instruction, which is designed well before the actual collaboration starts. Often, models of effective collaboration underlying these approaches specify a sequence of activities that students should engage in, and good collaboration is defined as adhering to this script (Kollar, Fischer, & Hesse, 2006). Collaboration skills are conceptualized in the form of internal collaboration scripts (Dillenbourg & Jermann, 2007), in analogy to the notion of scripts in cognitive psychology (Schank & Abelson, 1977). Support is provided by external collaboration scripts, i.e. by prescribing and sequencing specific activities (Kollar et al., 2006). Typically, such scripts provide fixed rather than adaptive support; however, newer approaches gradually and adaptively fade the external script in order to adapt support to students' knowledge and foster increasing self-regulation (Carmien et al., 2007).

Collaboration regulation approaches (Soller et al., 2005; also called management-based scaffolding by Zumbach et al., 2006), on the other hand, scan the ongoing collaboration process for specific indicators and provide support based on this analysis. Models underlying these approaches typically represent collaboration in the form of condition-action pairs, i.e. collaboration states (e.g. unequal participation) that call for specific actions (e.g. increase participation of less active group members). To enable adaptive support, collaboration regulation approaches specify observable indicators of critical collaboration states (e.g. discrepancy in number of learners' contributions), and the kinds of instructional support these indicators should trigger (e.g. prompts for increasing participation of less active learners). In this way, support can be generated at run-time during the ongoing collaboration. Ideally, when collaborating with such support for some time, collaborators should learn to recognize

critical collaboration states and engage in appropriate actions by themselves, i.e. to self-regulate their collaboration.

Which type of support is the most suitable also depends on the type of task collaborators are solving. Tasks that allow for defining a (recursive) structure of goals and subgoals may be best supported by collaboration structuring approaches (e.g. engaging in an academic debate by constructing a line of arguments, counterarguments, and syntheses; Weinberger et al., 2007). Other tasks, however, lack such a macro-structure and thus may benefit more from collaboration regulation approaches in which the ongoing collaboration is monitored for critical incidents that require specific actions (e.g. giving elaborated help whenever a partner asks for an explanation; Gweon et al., 2006). Our own experience with modelling and supporting the drawing of collaborative inferences showed that a fixed-sequence model was too simplistic for representing the dynamic nature of this skill. Fine-grained analyses of empirically observed collaboration helped to specify condition-action pairs that allowed for a more flexible representation of the individual and collaborative activities underlying the drawing of collaborative inferences, and eventually for the design of adaptive, collaboration regulation support.

Example: Modeling the Individual and Collaborative Activities Underlying Collaborative Inference Drawing

In line with prior findings on the effective structuring of group decision-making (Brodbeck et al., 2007), we started out with a model of collaborative inference drawing that assumed that students should first 1) pool their complementary, unshared information, and then should 2) look for connections that allowed for solution-relevant inferences before they 3) made a decision (Meier & Spada, in press). A corresponding collaboration script with an information-pooling phase, an information-integration phase, and a decision-making phase was designed. However, the script was not effective in increasing the number of students' collaborative

inferences. Further, an empirical analysis of the ways in which students actually drew collaborative inferences led us to revise our initial model. This analysis utilized a latent-class, multinomial-processing-tree model (Klauer, 2006), which allowed determining the fit between our hypothesized model and the empirical data while taking into account potential differences between groups of dyads. It showed that dyads who were particularly successful at drawing collaborative inferences appeared not to follow a fixed sequence of information pooling followed by information integration, but rather switched flexibly between the two.

The revised model therefore no longer assumed an optimal, global sequencing of activities, but rather specified three important strategies to be applied flexibly during collaboration (Meier & Spada, in press, submitted): The *information pooling strategy* entails informing one's partner about all potentially relevant information. Specifically, when students recall a piece of information that they think might be important for solving the problem, even though they cannot yet judge its true relevance or importance, they should ask their partner to help them make sense of it. This strategy is important because collaborators typically need their partner's complementary knowledge before they can make sense of their unshared distributed information. The *information take-up strategy* entails reacting promptly and attentively to new information learned during discussion. Specifically, when students notice their partner is telling them something new, they should take time to focus on and make sense of that information. Following this strategy is crucial to drawing collaborative inferences because otherwise students may be inclined to focus on the shared rather than the unshared information in a partner's contributions. Finally, the *information connection strategy* entails searching for interconnections between incoming pieces of information and one's prior knowledge about the task. Specifically, when students learn a new piece of information they should try to integrate it with what they already know. This strategy is important for drawing

any type of inference, but following it may be particularly challenging when drawing collaborative inferences in the dynamic context of an ongoing discussion.

Specifying Rules for Providing Adaptive Support Based on an Online Assessment of Collaboration Indicators

The final step towards designing adaptive collaboration support is the implementation of an online assessment and of a set of tutoring rules for generating just-in-time instructional communication (cf. Park & Lee, 2004). For the online assessment, observable indicators of critical incidents states have to be defined. The tutoring rules should then determine the kinds of support that specific incidents should trigger. Critical incidents could, for example, be impasses in important individual and collaborative activities underlying the targeted collaboration skill, e.g. knowledge sharing breakdowns (Soller, 2001) or dysfunctional communication (Gweon et al., 2006). These impasses could trigger instructions for engaging in remedial activities. Further, opportune moments for engaging in beneficial activities could be detected for the purpose of adaptive prompting, e.g. prompting for reflective discussion after a meta-cognitive conflict has been detected (Tedesco, 2003), or prompting for mutual elaborations after problem-solving hints have been given by a system (Diziol, Walker, Rummel, & Koedinger, this issue). In addition, activities that are particularly instrumental for achieving good problem solutions might be detected for the purpose of giving positive feedback in order to confirm and strengthen tentative, correct actions (Di Eugenio, Fossati, Ohlsson, & Cosejo, 2009). Future systems might also utilize observations of non-verbal behaviours (Bente, Senokozlieva, Pennig, Al-Issa, & Fischer, 2008) and physiological measures (Blascovich, & Seery, 2007) as indicators of emotional and motivational aspects of collaboration.

With regard to the kind of support that is provided based on an online assessment, a distinction has been made between adaptive systems that “mirror” collaboration and those that

provide guidance for collaboration (Soller et al., 2005). *Mirroring systems* feed back information on specific collaboration indicators to the group (e.g. number of contributions by each member; Kimmerle & Cress, 2008). This feedback is often provided in form of visualizations; sometimes information on the deviation from a desired state is provided as well (cf. Jermann & Dillenbourg, 2008). Thus, mirroring systems provide the group with information for their own regulation; they do not offer advice. *Guiding systems*, on the other hand, use online collaboration assessments to provide adaptive prompts and hints (e.g. Soller, 2001). The implementation of such guidance relies on specifying a set of tutoring rules and is often quite complex (Walker, Rummel, & Koedinger, submitted).

Example: Design of an Adaptive Inference Tutoring Tool

In our own research (Meier & Spada, in press, submitted) we decided to design a guiding system for facilitating students' application and internalization of the three collaboration strategies we had identified. We defined the conditions for applying the three collaboration strategies as the critical incidents to be assessed, and developed a set of pre-defined instructional messages to prompt for the associated actions. Specifically, we identified whenever a new piece of information was pooled during discussion in order to prompt collaborators to focus their attention on the new information (information take-up strategy) and to try to combine it with their prior knowledge about the case (information connection strategy). Further, we identified whether relevant pieces of information had not yet been discussed after some time in order to prompt the exchange of additional information (information pooling strategy). In addition, we also identified whenever a new solution-relevant inference was drawn in order to provide confirmatory feedback to collaborators. Because the resulting *inference tutoring tool* was only used with one particular task that had been designed specifically for training purposes, relevant information and inferences to be

detected in students' utterances could be defined in advance, facilitating the online assessment.

The inference tutoring tool was yet controlled by a human observer, constituting a wizard-of-oz design. The wizard used an observation matrix that allowed him to identify when relevant pieces of text information were mentioned and relevant inferences were drawn. Students received two kinds of informative feedback: *New information feedback* was given whenever one of them had pooled a new piece of information. This feedback drew students' attention towards the new information, and both prompted and facilitated inference drawing by indicating the owner of complementary information. Further, whenever a solution-relevant inference had been drawn, *complete inference feedback* was given, which informed students about the correctness of their inference and thus provided positive feedback for successful information connection. Towards the end of their discussion, collaborators additionally received *missing information prompts* and *missing information hints* to help them pool information and draw inferences that were still missing. These messages were adaptive to the observer's assessment of the discussion content, i.e. to gaps in the observation matrix representing the information and inferences students had discussed so far. A next step towards developing a fully automated version of the inference tutoring tool would be to implement an automated analysis of inference patterns in collaborators' dialogs, e.g. using natural-language-processing methods able to recognize a pre-defined set of relevant information categories (e.g. Rosé et al., 2008).

Evaluating the Effects of Adaptive Collaboration Support

Since the goal of adaptive collaboration support is to help students acquire collaboration skills, it should foster students' increasing self-regulation (Carmien et al., 2007). Therefore, it is sensible to test for both effects *with* and *of* (after) adaptive collaboration support (Kolodner

& Guzdial, 1996). One way to do so is to compare a training phase with adaptive support to a subsequent testing phase without support (Rummel & Spada, 2005). Of course, collaboratively solving a training task, even without any support, may already lead to an improvement of collaboration skills. To discern such basic training effects from more specific effects of collaboration support, training with collaboration support can be compared to training without collaboration support, and both can be compared to an untrained control condition (cf. Rummel & Spada, 2005). Further, to discern the benefits of adaptive over fixed support, a training condition with adaptive support can be compared to a training condition with fixed support (e.g. Diziol et al., this issue).

Example: A Training Experiment Evaluating the Adaptive Inference Tutoring Tool

The effectiveness of our inference tutoring tool was tested in the context of a training experiment that employed a training phase with collaboration support and a testing phase without collaboration support (Meier & Spada, 2008, submitted). The testing phase used the murder-mystery task; the training phase used a structurally similar task with a different cover story, i.e. diagnosing a patient with one out of several possible tropical diseases. The solution of both tasks depended on how effectively students integrated their complementary knowledge resources by drawing collaborative inferences. During the training phase, the amount of available support was varied between conditions: The *control condition* received no training at all. The *basic training* condition collaborated on the training case but did not receive any specific instruction on how to collaborate. The *instructed training* condition received a written explanation of the information pooling, the information take-up, and the information connection strategy before they solved the training task together. The *tutored training* condition also provided collaborators with this explicit strategy instruction; in addition, adaptive support for strategy application was delivered through the inference tutoring tool during students' collaboration on the training task.

Results from both the training and the testing phase showed that tutored training was the most effective in promoting collaborative inference drawing. In fact, dyads who had been guided by the inference tutoring tool during the training phase showed near optimal performance on the murder-mystery transfer task, when support from the tutoring tool was no longer available. Thus, these dyads acquired transferable collaboration skills that allowed them to self-regulate their collaboration during the testing phase. A comparison of the four conditions showed that tutored training was more effective than both basic and instructed training, and that trained conditions outperformed untrained controls. Thus, there was a positive effect of basic training, no additional benefit of explicit strategy instruction, and, most importantly, a positive effect of adaptive collaboration support over and beyond basic training and explicit instruction.

Conclusions

In this short review, we have outlined how the development of increasingly detailed and accurate models and the implementation of an online assessment of a specific collaboration skill, the drawing of collaborative inferences, enabled the design of an adaptive tutoring tool and thus an effective training method. Generalizing from our own experiences, and in line with previous research, we have described four steps in developing and testing adaptive collaboration support: deciding which collaboration skill(s) to support; conceptualizing the individual and collaborative activities underlying the targeted skill; specifying rules for providing adaptive support based on an online assessment of collaboration indicators; and evaluating adaptive collaboration support.

However, to account for the rapidly accumulating number of systems for adaptive collaboration support, further differentiations of this framework may be necessary. In

particular, more precise definitions of different types of *adaptiveness* might be useful. The adaptive collaboration support we have described in this review fits the definition of a *micro-adaptive system* according to Park and Lee's (2004) classification, i.e. a system that adapts instructional communication to an ongoing process analysis. However, there are other ways of realizing adaptive support. For example, micro-adaptive approaches might be complemented by what Park and Lee (2004) term *aptitude-treatment interaction systems*. These systems would fine-tune instructional support based on a pre-test of students' existing collaboration skills and preferences, and gradually fade support based on repeated assessments (cf. Carmien et al., 2007).

In our studies, we have focused on the collaboration skill of drawing collaborative inferences, by which collaborators co-construct genuinely new knowledge from complementary, unshared information. Our empirical findings show that the drawing of collaborative inferences is an important, but difficult collaboration skill. Integrating unshared, distributed information by means of collaborative inferences is likely to be more difficult than collaborators expect. Fortunately, adaptive collaboration support can go a long way in helping them acquire knowledge about beneficial collaboration strategies that they can apply in a flexible, self-regulated manner.

Commentary by Jim Blascovich

The authors present a particularly interesting and valuable contribution to the collaborative problem solving training literatures. Within a general framework of relevant steps in developing and testing adaptive collaboration support, they provide a detailed review of the conceptions, intuitions, logic, and reasoning, underlying their program of research. This basic research is focused on improving collaborative decision making in situations in which participants bring different but equally necessary pieces of information relevant to optimal

group decisions. This work is the type of work that is quite necessary for those interested in, or attempting to create on-line collaborative problem-solving agents such as intelligent tutors.

The authors make a strong case for truly collaborative problem solving, a category of problem solving that has the potential to take advantage of the whole (i.e., group) being greater than the sum of the parts. Their research not only identifies important problem areas for and relevant design steps in the development of adaptive tutoring systems, but also provides explicit guidance for necessary inclusions to such systems (e.g., carefully designed training cases, feedback based on the online assessment of critical collaboration states, etc.). In addition, they comparatively examine a number of training strategies, ones based on previous theory and basic research.

In order to complete the picture implied by the purpose of reported ideas and research, several challenges remain. First, it is not clear that the dyadic paradigm reported by the researchers generalizes to *n*-person groups regarding collaborative decision making. This, of course, is largely an empirical question. Second, one can think of other rationales and strategies for tutor/training tools that may prove better or worse than the ones compared here, for example, training future collaborative decision makers via some sort of modeling paradigm where they play "observer" roles in which they are privy to the entire information set, its distribution to another group and how such members actually underutilize important but distributed information. Finally, some mention, at least, of the difficult technical challenge of embodying maxims such as the authors' maxims within artificially intelligent adaptive tutoring systems. However, computer tutor system designers are likely to benefit greatly from the information provided in this paper.

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