Information Pooling and Processing in Group Problem Solving: Analysis and Promotion of Collaborative Inferences from Distributed Information

Anne Meier (anne.meier@psychologie.uni-freiburg.de)
Department of Psychology, University of Freiburg, Engelbergerstr. 41
79085 Freiburg, Germany

Hans Spada (hans.spada@psychologie.uni-freiburg.de)
Department of Psychology, University of Freiburg, Engelbergerstr. 41
79085 Freiburg, Germany

Abstract
An experiment was designed to study the drawing of inferences from a set of shared and unshared information in dyads collaborating on a specially developed task. Three types of inferences (common, individual, and collaborative) were distinguished based on information sharedness and distribution. In addition, two kinds of instructional support were explored in order to promote the collaborative drawing of inferences, in particular from unshared, distributed information. Results show substantial effects of information sharedness on all levels of the problem solving process (information pooling, inferences, and solution), as well as in a memory post-test. Instructional support led to more correct solutions and a stronger focus on inferences during discussion, but did not improve the drawing of inferences from unshared information. In-depth analyses of inference patterns in discussion shed further light on why inferences from unshared, distributed information are particularly difficult to draw. The reported findings go well beyond the existing literature on the effects of information sharedness that has primarily focused on “hidden profile” group decision tasks.

Keywords: problem solving; collaboration; inferences; hidden profiles

Group Problem Solving
Two heads are usually assumed to be better than one in solving knowledge-rich problems. For example, in today’s increasingly specialized organizations, complex problems are often assigned to teams whose members bring very diverse knowledge backgrounds into the problem-solving process. If members of these teams pool and integrate their complementary knowledge efficiently, high-quality problem solutions become possible that go beyond the capabilities of an individual problem-solver (e.g. Brodbeck, Kerschreiter, Mojzisch, & Schulz-Hardt, 2007; Kraut, 2003). To better understand the processes involved in group problem solving, many researchers apply concepts from cognitive psychology to group level cognition (Hinsz, Tindale, & Vollrath, 1997; Larson & Christensen, 1993; Mojzisch & Schulz-Hardt, 2006). Likewise, the present study examines information processing not at the individual, but at the group level. In particular, we focus on plausible inferences involved in constructing new shared knowledge at the group level. Our experiment was designed to trace the flow of information from an initial set of distributed information to an integrated problem solution building on inferences. In addition, we explored two kinds of instructional support in order to promote the collaborative drawing of inferences.

Information Sharedness
Groups start out with a certain amount of shared knowledge, i.e. knowledge that is known to all members, and a certain amount of unshared knowledge, i.e. knowledge that is only known to individual group members (Stasser & Titus, 1985). One of the most consistent findings in small group research has been that, when pooling and discussing information, groups tend to focus on shared information and neglect unshared information, thus failing to use their informational resources to their best potential. This so-called “information pooling effect” affects the amount of information that is pooled, the number of times a piece of information is repeated during discussion, and the influence it has on the final decision (Mojzisch, & Schulz-Hardt, 2006). The effect is usually studied in so-called “hidden profile” tasks, in which the relevant pieces of information are distributed in such a way that individual group members will tend to choose an inferior alternative, while the best alternative can only be found if all available information is pooled (Stasser & Titus, 2003). Typically, groups fail to detect the best solution in a hidden profile, falling short of their potential (for overviews see Mojzisch, & Schulz-Hardt, 2006; Wittenbaum, Hollingshead, & Botero, 2004).

The Role of Plausible Inferences
The voluminous body of existing research in the hidden-profile tradition has so far focused on decision tasks in which the mere aggregation of information is sufficient for finding a solution. However, more complex problems often require the group to go beyond the resources contributed by its members, producing synergy effects rather than aggregation (Kraut, 2003). Inferences are of particular importance in this respect, because they establish meaningful connections between individual pieces of information, and generate new knowledge that can be used to solve the problem at hand. For the purpose of the present study, the term “inference” is used in a broad sense, encompassing instances where at least two pieces of information are combined and, on the background of general
knowledge, transformed into a new piece of information (i.e. “plausible” inferences, cf. Black, Freeman, & Johnson-Laird, 1986; Collins & Michalski, 1989). For example, imagine that the readers of a murder mystery story have already learned that the victim of a crime was drugged around midnight, and some pages later read that a certain suspect has talked to the victim over a glass of whisky around that time. Very likely, these two pieces of information, together with their general background knowledge about murder mystery stories, will enable the readers to infer that the suspect might have drugged the victim’s whisky. While this inference does not yield certain knowledge (e.g. some other person might have slipped the drug into the whisky glass), it will nevertheless help to get a clearer picture of what happened, and, together with converging evidence, lead towards a solution of the case. In realistic group problem solving tasks (for example, in medical decision making teams discussing a patient), of course, many such inferences have to be drawn from a large set of information, that, most importantly, is distributed between group members.

In one study on group decision making, Fraidin (2004) deliberately implemented pairs of interdependent information items and thus required participants to draw inferences. However, the main focus of his study was on the effects of cognitive load and the perceived relevance of information on decision making, but not on the inference processes involved. The main goal of the present study, therefore, was to shed light on the effects of information sharedness and distribution on the inferences drawn in collaboration. In designing the experiment, three levels of information processing were taken into account. On the lowest level, we looked at information pooling, i.e. the amount of shared and unshared information brought into discussion. On a higher level of information processing, we focussed on the synthesis of new knowledge by drawing inferences. On the highest level, the decisions made by the group regarding the problem solution were assessed. Our main focus, however, was on the drawing of inferences.

**Studying Inferences from Shared and Unshared Information**

To study inference processes in group problem solving more closely, we developed a “hidden-inference” problem where the crucial achievement of the group is not only to detect a pattern of negative and positive pieces of information (as in a hidden profile task), but also to synthesize new knowledge from the available information by drawing inferences. Individual pieces of information in a hidden-inference problem point toward a wrong decision alternative, while only the resulting inferences enable the group to choose the right alternative. As in a classical hidden profile task, “sharedness” is manipulated at the level of individual information items. In addition, the distribution of unshared, interdependent pairs of information is manipulated.

To simplify matters, the problem is given to dyads instead of larger groups, i.e. each piece of information is known by either one or two persons. In this case, three types of inferences can be distinguished (Table 1):
- “collaborative inferences” from unshared information distributed between participants
- “individual inferences” from unshared information located with the same participant (“undistributed”), and
- “common inferences” from shared information, which both participants possess.

**Table 1: Visualization of collaborative, individual, and common inferences (adapted from Härder & Spada, 2004)**

<table>
<thead>
<tr>
<th>Information</th>
<th>Person A</th>
<th>Person B</th>
<th>Inference type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unshared</td>
<td></td>
<td></td>
<td>Collaborative</td>
</tr>
<tr>
<td>distributed</td>
<td></td>
<td></td>
<td>Individual</td>
</tr>
<tr>
<td>Unshared</td>
<td></td>
<td></td>
<td>Common</td>
</tr>
<tr>
<td>undistributed</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Shared</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

An unshared piece of information can only be entered into discussion by one person, while a shared piece of information can be entered by both. In line with the existing literature (e.g. Wittenbaum et al., 2004; Fraidin, 2004), it can be hypothesized that more shared than unshared, and more undistributed than distributed unshared information will be pooled. Regarding the three types of inferences (Table 1), common inferences should be the easiest type, because they can be drawn individually as well as collaboratively. Collaborative inferences, on the other hand, should be the hardest type, because they can only be drawn collaboratively during discussion.

**Instructional Support**

How can collaborators be supported in pooling the available information effectively and generating new knowledge from shared and, in particular, from unshared information? At the level of information exchange, there have been numerous attempts to eliminate the information pooling effect. However, as Stasser and Titus (2003, p. 310) conclude in their review, “(the) basic effect has been surprisingly robust.” Still, specific kinds of tools and instructions given to collaborators have had beneficial effects (see Brodbeck et al., 2007, for an overview). Most of these successful interventions have in common that they try to induce a critical, “problem-solving” attitude towards the task, and help collaborators to separate information-pooling from decision making. The effects of these kinds of interventions on the drawing of inferences have not yet been studied. However, from research on collaborative learning, we know that structuring collaboration by means of “collaboration scripts” is an effective means of fostering the generation of new knowledge (Kollar, Fischer, & Hesse, 2006;
Experiment

An experiment was conducted to study the effects of information sharedness on all levels of the problem solving process in a hidden-inference problem. In addition, three experimental conditions (scripted collaboration, informed planning, uninstructed control) were realized. Dyads collaborated over a desktop-videoconferencing system with shared applications that established controlled conditions in which all utterances and actions could be recorded.

Method

Materials The hidden inference problem was framed as a murder mystery task with four suspects, for whom participants were given a booklet with 24 solution-relevant information items (six four each of the four suspects) that were embedded in a larger story. Each participant received 8 unshared pieces of information, including two complete pairs of unshared undistributed information. All participants were told that their sets of information would differ to some extent, but they were not informed which pieces of information were shared and which were unshared.

After 30 minutes of individual reading time, each participant was asked to indicate how likely each suspect had committed the crime on a five-point rating scale from “very unlikely” to “very likely”, and to write down the name of the most likely suspect. Then, all materials had to be returned, and participants were allowed to discuss each other over the videoconferencing system. Dyads were given 50 minutes to discuss which of the four suspects had most likely committed the murder. They were asked to fill in the same questionnaire collaboratively that they had answered before individually. This time, they also had to provide a written justification for their decision.

To succeed, a dyad had to draw 12 inferences from both shared and unshared pieces of information, yielding the motive, the alibi, and one further piece of evidence for each of the four suspects. The task was constructed in such a way that, if all information items were pooled without drawing the appropriate inferences, the dyad was led to choose the wrong suspect. However, if all inferences were drawn, a second suspect turned out to be the only possible murderer.

The distribution of the information items allowed each dyad to draw four “common”, four “individual”, and four “collaborative” inferences. Three different text versions were realized in order to not confound the sharedness of information items and inferences with the implications of their specific content: Each of the 12 possible inferences was “common” in one text version, “individual” in another, and “collaborative” in a third version. All data were aggregated over these text versions.

Setting The desktop-videoconferencing system included two shared text editors which both participants could edit at the same time. One shared editor contained the decision questionnaire, the other served to produce the written justification. Both editors were available throughout the entire length of the discussion. Each person was also provided with a sheet of paper and a pencil for individual note-taking. All dyads received a short technical tutorial.

Instructional Support An uninstructed control condition was compared to two instructed conditions. Individuals in both instructed conditions were informed about typical task difficulties in advance of their collaboration on the murder mystery task: the existence of unshared information, the need to recall all information from memory during discussion, and the need to draw inferences in order to find a good solution. During their collaboration, dyads in the script condition were then guided by an electronic collaboration script that structured their collaboration: They were instructed to first pool the available information thoroughly in their shared text editor, and then engage in a phase of individual recall in order to complete the information pool. Then, dyads were told to search for interconnections between pieces of information, and to write down inferences regarding motives, alibis, and further evidence for all suspects. Finally, the script instructed them to summarize their information and make a decision. Dyads in the planning condition, on the other hand, were allowed to collaboratively construct their own collaboration script. Immediately after receiving the information on typical task difficulties, dyads in this condition were given 10 minutes to discuss how they wanted to structure their problem-solving process. They were encouraged to write down their plans in an additional shared text editor that stayed available for them during the rest of their collaboration.

Design Information sharedness (unshared distributed/ unshared undistributed/ shared) was realized as a within-subjects factor, and instructional support (control/ script/ planning) as a between-subjects factor.
Participants Fifty-four female students from various departments (except psychology) with an average age of $M=23.17$ ($SD=3.32$) years took part in the experiment. Participants were recruited by flyers and posters in university institutions. Each student was paid an honorarium of 15 Euros (about 19 US-Dollars) for their participation. Only students who did not know each other before collaboration were assigned to the same dyad. Dyads were randomly assigned to one of the three conditions. Post-hoc analyses on questionnaire data confirmed that conditions did not differ in participants’ age, academic grades, experience with computer use, or prior experience with murder mystery stories and films.

Dependent Variables

Discussion Content Dyads’ collaboration on the murder mystery task was videotaped and their discussions were later coded for relevant pieces of text information and inferences. Only correctly recalled information and correctly drawn inferences were coded. The codes yielded information on the number of discussed items and the total number of repetitions for all three types of information and all three types of inferences. The relative frequency with which items in a given category were pooled was then calculated by dividing the number of discussed items by the number of available items in that category (i.e. 8 for each type of text information, and 4 for each type of inference). In addition, the average number of repetitions was calculated by dividing the total number of repetitions for a given category by the number of discussed items.

Inference Patterns To study the ways in which inferences were actually drawn in more detail, we determined inference patterns for each of the 12 inferences. This was done by coding when and by whom the two interdependent pieces of information as well as the corresponding inference were brought into discussion.

Joint Solution The correctness of the solution, i.e. whether a dyad agreed on the correct suspect, as well as the probability rating given for the correct suspect served as outcome measures.

Memory Post-Test A memory post-test was designed to assess how much case information and how many inferences collaborators could recognize. It contained 48 sentences which comprised the 24 pieces of relevant text information, the 12 solution-relevant inferences, as well as 12 incorrect statements. The post-test was filled in individually directly after collaboration. All analyses were calculated with the mean value for each dyad and an n of 27.

Results

Discussion Content To determine the effect of information sharedness on the relative frequency of text information being pooled, an ANOVA was calculated with information sharedness (unshared distributed/ unshared undistributed/ shared) as within-subjects factor and experimental condition as between-subjects factor. There was a significant main effect of information sharedness ($F=11.44; p<.001$; partial $\eta^2=.32$), but no effect of experimental condition. Across all conditions, 71% of the unshared distributed, 84% of the unshared undistributed, and 93% of the shared text information was pooled during discussion (Table 2). This bias was most pronounced in the control condition; however, the interaction was not significant.

Table 2: Means and (standard deviations) for the relative frequency of text information being pooled

<table>
<thead>
<tr>
<th></th>
<th>Controls</th>
<th>Planning</th>
<th>Script</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unshared distr.</td>
<td>.69 (.21)</td>
<td>.71 (.26)</td>
<td>.72 (.19)</td>
<td>.71 (.21)</td>
</tr>
<tr>
<td>Unshared undistr.</td>
<td>.81 (.11)</td>
<td>.82 (.19)</td>
<td>.89 (.09)</td>
<td>.84 (.14)</td>
</tr>
<tr>
<td>Shared</td>
<td>.97 (.06)</td>
<td>.86 (.17)</td>
<td>.94 (.13)</td>
<td>.93 (.13)</td>
</tr>
</tbody>
</table>

A similar result pattern emerged for the relative frequency of inferences being pooled. An ANOVA revealed a significant main effect of information sharedness ($F=7.56; p=.001$; partial $\eta^2=.24$), but no effect of experimental condition. Across all conditions, 49% of the collaborative inferences, 65% of the individual inferences, and 79% of the common inferences were drawn (Table 3). Again, this bias was most pronounced in the control condition, but the interaction did not reach significance.

Table 3: Means and (standard deviations) for the relative frequency of inferences being pooled

<table>
<thead>
<tr>
<th></th>
<th>Collaborative</th>
<th>Individual</th>
<th>Common</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>.47 (.34)</td>
<td>.61 (.25)</td>
<td>.92 (.13)</td>
</tr>
<tr>
<td></td>
<td>.50 (.31)</td>
<td>.61 (.25)</td>
<td>.69 (.30)</td>
</tr>
<tr>
<td></td>
<td>.50 (.31)</td>
<td>.72 (.19)</td>
<td>.75 (.31)</td>
</tr>
<tr>
<td></td>
<td>.49 (.31)</td>
<td>.65 (.23)</td>
<td>.79 (.27)</td>
</tr>
</tbody>
</table>

ANOVARs over the average number of repetitions for the three types of text information and the three types of inferences, respectively, revealed no significant effects of information sharedness or experimental condition. A direct comparison between repetition rates for text information and inferences, however, showed that experimental conditions differed in their repetition rates for text information versus inferences: While dyads in the control condition repeated inferences less often than text information, this tendency disappeared in the two instructed conditions, who repeated inferences equally or even more often than text information (Table 4). However, this interaction did not reach the .05-level of significance ($F=3.09; p=.06$; partial $\eta^2=.21$).

Table 4: Average numbers of repetitions

<table>
<thead>
<tr>
<th></th>
<th>Controls</th>
<th>Planning</th>
<th>Script</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Information</td>
<td>3.28 (.61)</td>
<td>2.89 (.25)</td>
<td>2.87 (.34)</td>
<td>3.02 (.45)</td>
</tr>
<tr>
<td>Inferences</td>
<td>2.64 (.57)</td>
<td>3.01 (.68)</td>
<td>2.92 (.86)</td>
<td>2.86 (.70)</td>
</tr>
</tbody>
</table>
Inference Patterns Eight inference patterns were distinguished (Table 5). The three numerals represent the two interdependent pieces of information (first two positions) and the corresponding inference (last position): “0” signifies that the respective information or inference was not pooled, “1” signifies that it was, and “2” signifies that it was provided by the collaboration partner of the person who contributed the first piece of information.

Table 5: Absolute frequencies of inference patterns for the three inference types (n= max. 108 for each inference type).

<table>
<thead>
<tr>
<th>Inference type</th>
<th>Complete inference patterns</th>
<th>Incomplete inference patterns</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1-1-1</td>
<td>1-1-2</td>
</tr>
<tr>
<td>Collaborative</td>
<td>3’</td>
<td>3’</td>
</tr>
<tr>
<td>Individual</td>
<td>61</td>
<td>6</td>
</tr>
<tr>
<td>Common</td>
<td>50</td>
<td>9</td>
</tr>
<tr>
<td>Collaborative</td>
<td>14</td>
<td>34</td>
</tr>
<tr>
<td>Individual</td>
<td>6</td>
<td>23</td>
</tr>
<tr>
<td>Common</td>
<td>2</td>
<td>11</td>
</tr>
</tbody>
</table>

* These “impossible” patterns were probably miscoded due to information being entered into the shared text editor before being taken up in discussion.

For the complete inference patterns, i.e. cases in which the appropriate inference was in fact stated during discussion, two patterns clearly dominated across all experimental conditions: the “same person” pattern (1-1-1), where both pieces of information and the corresponding inference were entered by the same person, and the “completion” pattern (1-2-2), where a second person contributed a matching piece of information together with the appropriate inference. Individual inferences provide the clearest picture: as one would expect, the “same person” pattern was dominant (61 out of 70 complete inferences). For collaborative inferences, which could not be drawn individually without prior information exchange, the majority (31 out of 54 complete inferences) followed the “completion” pattern. Interestingly, it occurred nearly twice as often as the equally possible “turn-taking” pattern (1-2-1). For common inferences, the “same person” pattern clearly dominated (50 out of 84 complete inferences), with “completion” as the second most frequent pattern (again, about twice as frequent as the “turn-taking” pattern). Thus, the “same-person” pattern emerged as the most frequent one whenever it was possible, while among the collaborative inference patterns “completion” was dominant. Closer analyses revealed that in more than half of the cases following the “same person” pattern (69 out of 114), both pieces of text information as well as the inference were introduced within the same minute; i.e. they were introduced as a whole. Similarly, in the majority of cases (36 out of 49) following the “completion” pattern, the second piece of information was entered within the same minute as the inference.

For incomplete inferences, the most frequent pattern across all three inference types was the “incomplete information” pattern (1-0-0), where the corresponding second piece of information that would have allowed for the inference to be drawn was not brought into discussion. Overall, these observations show that, if a “matching” piece of information was brought into discussion at all, it was very likely to be entered together with the corresponding inference. Furthermore, both the matching piece of information and the inference itself were mostly brought into the discussion by the same person, usually in close temporal proximity.

An analysis of inference patterns according to experimental condition revealed that the proportion of complete inferences following a collaborative pattern (i.e. 112, 121, or 122) was higher for dyads in the two instructed conditions as compared to dyads from the control condition (M= .47 for script and .46 for planning vs. M= .37 for controls). However, this difference did not reach significance due to high variability within the conditions (script: SD=.11; planning: SD=.27; control: SD=.19).

Joint Solution A large majority, i.e. 24 out of 27 dyads, identified the correct person as the guilty suspect. All three dyads who solved the case incorrectly were from the control condition. A Chi-Square test showed that this difference between experimental conditions was significant ($\chi^2= 6.75; p= .03$). Dyads in the control condition also gave lower probability ratings (M= 4.3 on a scale from 1 to 5) for the correct suspect than the other two conditions (M= 5.0 for the planning and M= 4.8 for the script group; n.s.). Experimental conditions did not differ in the number of participants per dyad who preferred the correct solution prior to discussion ($\chi^2= 1.04$ and $p= .32$); and 32% of the participants in the script group (n.s.) preferred the correct solution prior to discussion ($\chi^2= 1.04$ and $p= .32$), thus the difference between experimental conditions is likely to have its origin in the discussion itself. This interpretation is corroborated by the fact that a dyad’s probability rating for the correct suspect correlated with the number of inferences drawn during discussion ($r=.3; n.s.$), in particular with the number of collaborative inferences ($r=.42; p=.03$).

In the written justification of the solution, a pattern similar to the one found for the discussion content emerged: Dyads named 38% of the unshared distributed, 48% of the unshared undistributed, and 51% of the shared pieces of information (F= 3.36; p= .04; partial $\eta^2= .12$); and 32% of the collaborative, 42% of the individual, and 44% of the common inferences (n.s.). Again, there were no effects of experimental condition and no interactions.

Memory Post-Test Participants’ ability to identify text information and solution-relevant inferences in the knowledge post-test, too, differed depending on the sharedness and distribution of information. Across all conditions, participants correctly recognized 79% of the unshared distributed, 86% of the unshared undistributed,
and 97% of the shared text information ($F= 17; p< .001; partial \eta^2 = .42$), and identified 67% of the collaborative, 71% of the individual, and 76% of the common inferences (n.s.). There were no effects of experimental condition and no interactions.

**Discussion**

Results of the experiment show substantial effects of information sharedness and distribution on all levels of the problem solving process: Dyads discussed more shared than unshared, and more unshared undistributed than unshared distributed information. They also drew more inferences from shared information (common inferences), while inferences from unshared distributed information (collaborative inferences) were the hardest to draw. The same pattern was found in the written solution produced by the dyad, as well as in an individual memory post-test. These effects go well beyond the existing literature on the effects of information sharedness in “hidden profile”-like situations on group information processing. In particular, the drawing of collaborative inferences from unshared distributed information emerges as an interesting topic for future studies on group problem solving. While these inferences were the most difficult to draw, they also proved to be particularly indicative for the quality of the solution in our study. However, supporting groups in drawing these collaborative inferences is no trivial task. On the one hand, both instructional support measures that were employed in our study (scripted collaboration and informed planning) succeeded to significantly improve the number of correct solutions, probably mediated by a stronger focus on inferences versus text information, and a more collaborative approach towards the drawing of inferences in some dyads. On the other hand, instructional support mitigated the bias towards shared information only to a small degree. In particular, the number of conclusions drawn from unshared distributed information was mostly unaffected by instruction. Further approaches towards supporting collaborative inferences might profit from more detailed analyses of the interplay between individual and group-level information processing. For example, our analysis of inference patterns has shown that a “matching” piece of information is usually entered by the same person as (and in close temporal proximity to) the corresponding inference. Thus, the most crucial part of a collaborative inference seems to be an individual’s realization that two pieces of information “belong together”. Further research is needed to explore how this aspect of individual information processing might be supported in order to improve group-level problem solving.

**Acknowledgments**

This work is being funded by the Virtual Graduate School “Knowledge Acquisition and Knowledge Exchange with New Media” of the German Science Foundation (www.vgk.de).

**References**


