

# Can Simple Group Heuristics Detect Hidden Profiles in Randomly Generated Environments?

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Research on the hidden-profile effect (Stasser, 1992) has revealed that groups often fail to detect the choice alternative with the highest sum score if the individual group members' information points to another alternative. We conducted a simulation study in which we randomly generated distributions of information such that they did or did not contain a hidden profile. The simulated groups solved the tasks by applying a unit weight linear model or a fast and frugal heuristic (Minimalist or Take The Best). Overall, a communication-based lexicographic heuristic performed best across the different environments. This fast and frugal heuristic makes cue-wise comparisons of alternatives while pooling information during group discussion. Moreover, results show that performance depends on whether group members share and exchange information on valid or on invalid cues. Directions for future research are discussed.

*Keywords:* group decision making, hidden-profile effect, shared information, decision strategies, unit weight linear model, lexicographic heuristic

When facing a decision task, a group usually has more relevant information than does each of its individual group members, providing a potential advantage for group decision making. In this context, the claim is often made that a group can only gain from its available expertise if group members extensively pool their unique knowledge, and that good group decisions hence require exhaustive information processing. However, empirical research has shown that groups often do not exchange all available pieces of information during the decision process. In particular, groups are more likely to discuss information that is already known to all group members at the outset of the group decision process (shared information), whereas unique information that is only held by single group members (unshared information) is less likely to be mentioned

during discussion (Gigone & Hastie, 1997; Stasser & Titus, 1987; Wittenbaum & Stasser, 1996).

Studies on the hidden-profile effect (Stasser & Titus, 1985) indicate that such behavior is highly maladaptive because it prevents groups from arriving at a fully informed decision. The hidden-profile paradigm describes a situation in which a group has to select one of several alternatives. There is one alternative that has a higher sum score (i.e., a higher difference between the number of positive and negative attributes) than any other alternative. However, this profile is hidden to individual group members. Specifically, the information items about the alternatives are distributed among the group members in a biased way such that each individual group member has more positive (and fewer negative) pieces of information

on another alternative. In such a situation, groups only rarely detect the hidden profile, that is, select the alternative with the highest score (for an overview, see Stasser & Birchmeier, 2003; Wittenbaum & Stasser, 1996).

The robust empirical finding that a lack of individual knowledge may prevent a group from detecting a hidden profile is often counted as strong evidence for the more general claim that extensive information search and exchange is a prerequisite for good group decisions. This claim rests on the intuitive assumption that group decisions could not be affected by the distribution of information among the group members if they always exchanged and integrated all pieces of information that are known by at least one group member. In line with this reasoning, recent research has focused on variables that moderate the sampling advantage of shared information and on interventions that may stimulate the exchange of unshared information. However, this research revealed that most interventions have only marginal effects – the hidden-profile effect as well as the sampling advantage of shared information seem to be very robust empirical phenomena (e.g., Larson, Foster-Fishman, & Keys, 1994; Mennecke, 1997; Stasser, Stewart, & Wittenbaum, 1995; Stasser, Taylor, & Hanna, 1989; Stewart, Billings, & Stasser, 1998; for effective interventions see Hollingshead, 1996; Schittekatte & van Hiel, 1996).

Whereas research on the hidden-profile effect has focused on factors that affect the amount of pooled information, the question of how the available information should be processed and integrated into a decision has been addressed in only a small number of studies (e.g., Chernyshenko, Miner, Baumann, & Sniezek, 2003; Stasser, 1988). This is particularly surprising as it is evident that different decision strategies can lead to different decisions. Moreover, recent research on fast and frugal heuristics suggests that using less information does not necessarily lead to worse decisions. Under specific conditions these heuristics can even outperform computationally more demanding strategies (Czerlinski, Gigerenzer, & Goldstein, 1999; Hoffrage & Reimer, 2004). In the present work we apply this framework of fast and frugal heuristics as proposed by Gigerenzer, Todd, and the ABC Research Group (1999) to group decision making by simulating the performance of compensatory and noncompensatory strategies in various information environments. The main goal was to see whether there are heuristics that are capable of detecting hidden profiles without requiring exhaustive information processing. Note that this is a prescriptive question and that our agenda is not to account for existing empirical data. Given the difficulty that groups have pooling information (e.g., Brodbeck, Kerschreiter, Mojzisch, Frey, & Schulz-Hardt, 2002; Schulz-Hardt, Jochims, & Frey, 2002; Stasser & Titus, 1985, 1987; for a recent review, see

Stasser & Birchmeier, 2003), and the time-consuming nature of communicating and processing unique information items known only to individual group members, it may turn out to be useful to see whether fast and frugal group heuristics achieve a good performance with this kind of task.

The paper is structured as follows: We first introduce the hidden-profile effect in more detail and briefly review the major theoretical approaches to group decision making within this paradigm. In the following Method section we describe the details of our simulations: We specify the strategies that we evaluated and describe the procedure that we used to generate the environments in which the strategies were tested. The Results section commences with some descriptive statistics capturing aspects of the environments that we created. We then report how the strategies performed. To explore the ecological rationality of the decision strategies, that is, their sensitivity to particular structures of information, we have analyzed and report the results separately for environments that contained a hidden profile and those that did not. In addition, we have tested how the quantity and quality of shared information affects the strategies' performance. Finally, we discuss various implications of the present work.

## The Hidden-Profile Effect

Consider the following situation: A four-member personnel committee has to decide which of two candidates, A or B, is better suited for a position. Each candidate is described on several dimensions; for instance, he or she may have special computer skills or speak a particular foreign language. For the sake of simplicity, we are only considering those qualifications or features, henceforth called *cues*, that support a candidate if they are present, and speak against a candidate if they are absent. We denote present qualifications with a cue value of “+1” (e.g., if a candidate has special computer skills), absent qualifications with a cue value of “–1” (e.g., if a candidate lacks special computer skills), and qualifications for which it is not known whether a candidate possesses them with a cue value of “0”. Table 1 shows a distribution of information in which all cue values are positive. The two columns list the cues on which the candidates have positive cue values and the four rows depict the knowledge of individual group members at the outset of the group decision process. Each group member receives information that for Candidate A, Cues 1, 2, and 3 are present. In addition, each group member receives one piece of information about Candidate B. Specifically, the Members 1, 2, 3, and 4 receive information that the Cues 4, 5, 6, and 7 are present, respectively.

Table 1  
*A Hidden Profile Created by a Distribution of Information on Seven Features or Cues*

Group member	Knowledge about Candidate A	Knowledge about Candidate B	Decision
Member 1	Cues 1, 2, 3	Cue 4	Candidate A
Member 2	Cues 1, 2, 3	Cue 5	Candidate A
Member 3	Cues 1, 2, 3	Cue 6	Candidate A
Member 4	Cues 1, 2, 3	Cue 7	Candidate A
Omniscient Member	Cues 1, 2, 3	Cues 4, 5, 6, 7	Candidate B

*Note.* Each cue speaks, if present, in favor of the particular candidate. For Candidate A, the Cues 1, 2, and 3 are present (this knowledge is shared by all group members), and for Candidate B, the Cues 4, 5, 6, and 7 are present (this knowledge is unshared by group members).

Note that the four committee members have the same knowledge on Candidate A (shared information), whereas their knowledge on Candidate B is unique (unshared information).

Assume that the group members will share all of their knowledge or, alternatively, tell it to a fifth, imaginary group member, henceforth referred to as the *omniscient member*. This omniscient group member would have knowledge about the presence of three positively valued cues describing Candidate A and four positively valued cues describing Candidate B.

In the example shown in Table 1, it is hidden to each group member that Candidate B has the highest overall sum score. If group members form an individual decision on the basis of their individual knowledge by computing the sum score for each candidate (i.e., by applying a unit weight linear model that gives an equal weight to each cue), each individual member will prefer Candidate A, whereas the omniscient group member would prefer Candidate B. In the present paper we adopt the standard that has been established in the literature on the hidden-profile effect; namely, we consider the candidate with the highest sum score to be the best one (see Footnote 1 in Stasser & Titus, 1985; also see Reimer & Hoffrage, 2003). In other words, the decision of an omniscient group member applying a unit weight linear model serves as the gold standard and provides the best solution by definition.

Empirical studies have repeatedly shown that groups only rarely identify the alternative with the highest score if its profile is hidden. For example, in their classic study, Stasser and Titus (1985) used a three-alternative task in which each alternative was described on 16 cues. The candidate with the best profile was Candidate B, who was described by 8 positive, 4 neutral, and 4 negative cues. Both Candidate A and Candidate C were described by 4 positive, 8 neutral, and 4 negative cues. Thus, unlike in our example, which used only positive cues (i.e., those that are in favor of the candidate if present), Stasser and Titus also included neutral and negative cues. As in our simple exam-

ple, this information was distributed among members of four-person groups in a biased way: Each individual group member received only 2 of the 8 positive cues on Candidate B (but the full set of information about the 4 neutral and the 4 negative cues) and only 1 of the 4 negative cues on Candidate A (but the full set of information about the 4 positive and the 4 neutral cues). As a consequence, the individual group members tended to prefer Candidate A: Before discussion, only 25% of the members favored B; after discussion, 24% of the groups chose B. Conversely, when each group member received all pieces of information, that is, when the candidate with the highest sum score was not hidden, 67% of the members favored B before discussion and 83% of the groups chose B after discussion.

## Explanations for the Hidden-Profile Effect

In the literature on the hidden-profile effect, two main explanations have been proposed that may help us understand why shared information might have a stronger impact on a group's decision than unshared information. These explanations are in accordance with the distinction between social communication and social combination processes (Baron, Kerr, & Miller, 1992). The social communication approach studies how group decisions are affected by the exchange of information and by features of group discussion. This approach explains the hidden-profile effect by the sampling advantage of shared information (Stasser & Titus, 1985): Because at the outset of the group decision process, each individual group member knows more information items that are in favor of Candidate A than in favor of Candidate B (see Table 1), the information on Candidate A is also more likely to be communicated during discussion. The group fails to integrate the unique information on Candidate B and thus will not detect the hidden profile.

The social combination approach conceptualizes group decision making as a process of integrating individual decisions rather than individual contributions to a discussion. According to this approach, groups are unable to detect a hidden profile because shared information has a larger impact on the individual decisions (Gigone & Hastie, 1997). In our example, there might be unanimity at the outset of the decision process that Candidate A is better suited for the position, and thus there might be no need for the group to exchange any information at all, in particular if the group's task consists in making a joint decision that does not need any justification. Once group members have formed an individual decision, they tend to stick to this original decision and misinterpret information that is inconsistent with their already formed preference (Greitemeyer & Schulz-Hardt, 2003; Reimer, 1999).

Some explanations involved combining these two approaches, which do not contradict each other, by testing whether the effect of discussion content on a group's decision is mediated by a change of the individuals' decisions (Stasser, 1992), and whether the effect of the initial distribution of individual decisions on the group decision is mediated by the content of the discussion. For an extensive discussion of the interplay of these two approaches to group decision making in general, see Baron et al. (1992), and in the context of the hidden-profile effect in particular, see Stasser (1988, 1992) and Winquist and Larson (1998).

All of these explanations of the hidden-profile effect – the one offered by the social combination approach, by the social communication approach, and those based on an integrative model – share the assumptions that the candidates are evaluated one after the other (alternative-wise processing of information), and that a compensatory decision strategy is applied to determine a sum score for each of them. We extend this line of research by applying simple, noncompensatory heuristics to this task. These heuristics process information cue-wise, that is, they sequentially look up cues on which they compare all candidates. The idea that individual group members might use noncompensatory heuristics has already been considered (Gigone & Hastie, 1997; Kerr & Tindale, 2004; Stasser, 1988, 1992). However, to the best of our knowledge the present paper is the first in which such heuristics are specified and systematically evaluated in the context of hidden-profile environments (for simple group heuristics in other domains, see Reimer & Hoffrage, 2003, 2004; Reimer & Katsikopoulos, 2004).

## Method

We conducted a Monte Carlo study in which we simulated group decision making in different environments, that is, with different distributions of information about candidates across group members. Simulations provide a powerful tool, not only for generating new research questions but also for comparing the outcome of different decision strategies across a wide range of environments (for simulations in the domain of group decision making, see Gigone & Hastie, 1996; Hastie & Stasser, 2000; Johnson, Budescu, & Wallsten, 2001; Stasser, 1992). In our simulations, we used a standard task that has also been used in previous research (Davis, 1973; Stasser & Titus, 1985), which we introduced above: A four-member personnel committee has to decide on which of three candidates is best suited for a position. In accordance with studies on the hidden-profile effect, no outside criterion exists, and the crucial question is whether the simulated group will choose the candidate with the highest sum score. How can this task be solved?

According to the social combination approach (Baron et al., 1992; Davis, 1973), members first reach their decisions independently before they subsequently exchange these individual decisions and combine them into a group decision. According to the social communication approach, in contrast, individuals do not exchange their individual decisions, but they engage in the exchange of information, which then forms the basis for a group decision. In the following, we will first introduce decision strategies that fit under the social combination approach, and we will subsequently adapt these strategies to be used within the social communication approach.

## Decision Strategies within the Social Combination Approach

Social combination strategies integrate individual decisions into a group decision. In the simulations reported below, we compared the performance of the following three strategies that can be used by individual group members: (1) a unit weight model, (2) a simple heuristic that eliminates candidates on the basis of randomly drawn cues (the Minimalist heuristic), and (3) a lexicographic heuristic that looks up cues according to their validity (the Take The Best heuristic). How do these strategies operate?

*Unit weight model (UWM):* This strategy computes an overall score for each of the candidates by summing up the cue values on all available cues, which amounts to subtracting the number of negative cue values from the number of positive cue values, while ignoring the number of unknown cue values. It then decides in favor of the candidate with the highest overall sum score. If an outside cri-

terion existed, UWM would predict that the candidate with the highest sum score has the highest criterion value. As Dawes and Corrigan (1974) have shown for out-of-sample predictions, specifically, in cross-validation, linear models with unit weights perform astonishingly well when compared to more complex weighting schemes, such as those obtained by multiple regression.<sup>1</sup> Note that UWM uses all available information and is compensatory in that positive values on some cues can be compensated for by negative values on other cues.

*Minimalist (MIN):* In contrast to UWM, the heuristics defined by Gigerenzer et al. (1999) search for information cue-wise, that is, they compare the candidates on a given cue. Compared with compensatory decision strategies like UWM, these heuristics are simpler to execute because they do not require any computation such as computing sum scores, and they are more frugal because they stop the information search as soon as one cue that discriminates between the alternatives has been found. The simplest cue-based heuristic is the Minimalist, which was originally designed for pair comparison (Gigerenzer et al., 1999). We adapted this heuristic here for the task of selecting one of three candidates.

Heuristics can be defined by their building blocks, which precisely describe how information is searched for (the search rule), when the information search is stopped (the stopping rule), and how the information is integrated into a decision (the decision rule). MIN consists of the following building blocks:

*Search rule:* Draw a cue randomly – among those that have not yet been used – and look up the cue values of all candidates who are still in the choice set.

*Stopping rule:* Eliminate all candidates who have a lower value than the candidate with the maximum value. Unknown cue values are treated as a third category; that is, two candidates with the values “1” and “0” as well as another two with the values “–1” and “0,” respectively, are assumed to be discriminated. If only one candidate re-

mains or if all cues have already been looked up, then stop the search and proceed with the next step; otherwise search for another cue (for other discrimination rules and a discussion of how different discrimination rules affect performance of heuristics, see Hoffrage, Hertwig, & Czienskowski, 2003).

*Decision rule:* If all but one candidate are eliminated after the search has been stopped, predict that this candidate is the one with the highest sum score. If there is more than one candidate left but the search cannot be continued because all cues have already been looked up then choose randomly among the remaining candidates.

*Take The Best (TTB):* This heuristic differs from MIN only in that the cues are not drawn randomly but in an order established by their (perceived) validity. The validity of a cue is defined as the percentage of correct inferences in the set of pairs in which the cue discriminates (Gigerenzer, Hoffrage, & Kleinbölting, 1991; for other definitions see Martignon & Hoffrage, 2002). To determine whether an inference is correct, one needs to have an outside criterion. Because we adopted the standard of the research tradition on the hidden-profile effect, however, there was no outside criterion in the present task. In this situation, we used the candidates' sum scores, that is, the sum of all cue values, as a substitute for the outside criterion and as a basis to compute the validity of each cue.<sup>2</sup> The stopping rule and the decision rule for TTB are the same as for MIN, but the search rule now reads: Pick the most valid cue among those that have not yet been used and look up the cue values of all candidates who are still in the choice set.

These decision strategies (UWM, MIN, and TTB) are designed for individuals and thus may be used by the group members to form individual decisions that are based on their individual knowledge. Then, the question arises: How can these individual decisions be integrated into a joint group decision? Research on the social decision scheme approach (Baron et al., 1992; Davis, 1973; Hinsz, Tindale, & Vollrath, 1997; Kerr & Tindale, 2004; Laughlin & Ellis, 1986) has consistently shown that groups adapt

1 Dawes and Corrigan (1974) also included a weighted additive model (WADD) in their analyses. As in linear regression, WADD weights each cue by its predictive power (or by its validity, respectively; see Reimer & Hoffrage, 2004). In Dawes and Corrigan's analyses, an outside criterion existed and it therefore made sense to compare different weighting schemes.

In the present case, however, in which UWM serves as the gold standard, no other weighting scheme can outperform UWM (at least in a situation with full knowledge about all cue values). For this reason we did not include a weighted additive strategy in our simulations (in Reimer and Hoffrage, 2004, we introduced an outside criterion and included a linear model that weighted cues by their validity; for an experimental study considering different weighting schemes, see Gigone & Hastie, 1997).

2 Validity was computed across all possible comparisons within each environment, that is, within each triplet of candidates. Hence, the validities could be either 1 (if the cue values for the candidate with the highest, second highest, and lowest sum score were either 1, 1, 0, respectively, or 1, 0, 0, respectively), .5 (if the values were either 0, 1, 0, or 1, 0, 1), or 0 (if the values were either 0, 0, 1, or 0, 1, 1). The rank ordering of cues was known to all simulated group members, irrespective of the cue values that they had available. In other words, we assumed that there was agreement among the group members on what the good, neutral, and misleading cues were, and that group members' cue orderings were consistent with the true state of affairs in each of the task environments.

their social combination rule according to the task at hand. In general, if a task has a correct solution (intellective task) that is known by at least one group member who is able to demonstrate its correctness (Laughlin & Ellis, 1986), then the likelihood is high that this group member's preference will dominate the group decision (truth wins scheme). In contrast, if a task has no demonstrably correct solution (judgmental task), groups are more likely to apply a voting rule (majority scheme; see Davis, 1992, for an overview; also see Adamowicz et al., 2004; Reimer & Katsikopoulos, 2004; Tindale, Smith, Thomas, & Filkins, 1996).

The current task consists of choosing a candidate for a job position. This task can be described as a judgmental task that has no demonstrably correct solution because there is no objective outside criterion. For this reason, the use of the majority rule seems to be most likely (see Gigone & Hastie, 1997, for a related argument). The simulated groups thus used the following combination rule:

*Majority rule (Maj):* Decide in favor of the candidate who receives the majority or plurality of votes from the individual group members. If there is a tie with respect to the number of votes then adopt the decision of one randomly chosen group member (majority, plurality otherwise, proportionality otherwise, henceforth denoted as *majority* or *Maj*).

We simulated individuals (Ind) who used the UWM, MIN, or TTB (henceforth, Ind-UWM, Ind-MIN, and Ind-TTB, respectively). The simulated groups were homogeneous with respect to the strategy applied, that is, all group members used the same strategy to arrive at their individual decisions. These decisions were then integrated into a group decision on the basis of the majority rule (Maj-UWM, Maj-MIN, and Maj-TTB).

## Decision Strategies within the Social Communication Approach

An alternative way for a group to reach a joint decision is to exchange information and to generate a decision on the basis of the cue values that have been exchanged during the group discussion. This does not require group members to form initial individual decisions, even though such decisions may exist and the probability that group members will communicate a particular cue value may depend on their individual decisions (Gigone & Hastie, 1997; Winquist & Larson, 1998). One reasonable way to implement decision strategies based on the social communication approach consists in simulating groups that behave like an individual who has access to all of the information that was mentioned in the discussion. Such a decision strategy would require a sampling rule that specifies what information is communicated during the group discussion,

and a decision rule that specifies how this information is integrated into a group decision. Both kinds of rules can be adapted from the strategies used by individuals.

*Com-UWM:* According to this strategy, each group member communicates all available pieces of information on a particular candidate, and the group subsequently sums up all of these cue values. The same procedure is repeated for the other candidates, and the group finally selects the candidate with the highest sum score. Thus, Com-UWM always yields the same decision as the omniscient group member using UWM (Omni-UWM) and will thus also always detect a hidden profile. According to the literature on the hidden-profile effect, this decision strategy can be seen as an ideal that guarantees that a group integrates all available pieces of information. If groups applied this decision strategy their decisions would not be affected by the distribution of information among their members.

*Com-MIN:* This strategy assumes that one group member draws the group's attention to one cue on which this member has at least some knowledge. The group then compares the candidates on this cue by pooling all available cue values. More precisely, Com-MIN may be described by the following building blocks:

*Search rule:* Draw a group member randomly. This group member randomly draws one cue from among those that have not yet been used and on which this group member has information about at least one candidate. The group then looks up and exchanges the cue values of all candidates who are still in the choice set.

*Stopping rule:* Eliminate all candidates who have a lower value than the candidate with the maximum value. If only one candidate remains or if all cues have been looked up already, then stop the search and proceed with the next step; otherwise search for another cue.

*Decision rule:* If all but one of the candidates are eliminated after the search has been stopped, predict that this candidate is the one with the highest sum score. If more than one are left but the search cannot be continued because all cues have already been looked up, then choose randomly among the remaining candidates.

Thus, the building blocks of Com-MIN are very similar to the building blocks of Ind-MIN. The main difference is that the group first has to select a group member who randomly chooses a cue. Consequently, only those cues on which this group member has any information can be chosen. According to Com-MIN, group members are chosen randomly, which is a reasonable procedure if no systematic differences in participation rates (due, for instance, to status or expertise) are expected.

*Com-TTB:* This strategy proceeds like Com-MIN, except that the group member who has been drawn randomly will not draw a cue randomly but will pick the cue with the highest validity among those that have not yet been

used by the group and on which this group member has information about at least one candidate.

Figure 1 gives an overview of the different decision strategies and conditions that we used in our simulations. The lowest unit in which a strategy can be applied is the individual (Ind-UWM, Ind-MIN, and Ind-TTB). A special case is the omniscient individual (Omni) who also can use any of the strategies described above (Omni-UWM, Omni-MIN, and Omni-TTB). This omniscient individual knows everything that any one of the group members knows and can be interpreted as a control condition. Using this terminology, a hidden profile can be defined as a distribution of information in which no individual group member who applies a unit weight model (Ind-UWM) makes the same choice as Omni-UWM (which provides, by definition, the correct solution). The three decision strategies (UWM, MIN, TTB) that specify how information across cues is processed were fully crossed with the four units of analysis that specify how information across group members is processed (Omni, Ind, Maj, Com).

Which candidates will the various strategies select in the example of a hidden profile introduced in Table 1?

While Omni-UWM will choose Candidate B, each group member that applies Ind-UWM will choose Candidate A, thus failing to detect the hidden profile and to select the best candidate. As a consequence, Maj-UWM, which aggregates the decisions of the individual members, will also fail. If a group member draws cues randomly (Ind-MIN), there is a 1 in 4 chance (i.e., 25%) that this member will decide for Candidate B. If these individual decisions, achieved by Ind-MIN, are integrated into a group decision by using a majority rule (Maj-MIN) the chances that the group will choose the best candidate are higher than for Maj-UWM but still worse than chance. Chances that Omni-MIN will choose Candidate B are 4 out of 7 (i.e., 57%). How does Com-MIN perform? Com-MIN first chooses a group member randomly who then draws a cue randomly. In our example, the chances that Com-MIN will choose Candidate B are 1 out of 4 (i.e., 25%), and thus Com-MIN yields the same performance as Ind-MIN. If the individuals have reliable knowledge about cue validities (Ind-TTB, Maj-TTB, and Com-TTB) groups will always decide in favor of Candidate B. This is because the cues that describe Candidate B have a validity of 1, whereas those

### *Compensatory decision strategy*

**UWM** The unit weight linear model sums up cue values of each alternative and chooses the alternative with the highest sum score.

### *Noncompensatory heuristics*

**MIN** The Minimalist draws cues randomly. Alternatives that do not have the highest observed cue value are eliminated. Information search stops as soon as one alternative remains.

**TTB** Take The Best is a lexicographic heuristic that differs from MIN only in that it draws cues according to an order established by their validity.

### *Conditions and units of analysis*

**Omni** Control condition, in which decisions are made by an individual that has access to all available information at the outset – the omniscient group member.

**Ind** Decisions made by the individual group members.

**Maj** Group decisions based on a majority/plurality/proportionality rule – social combination approach.

**Com** Group decisions based on information that is exchanged during discussion – social communication approach.

Figure 1. Decision strategies and conditions used in the simulations.

that describe Candidate A have a validity of 0 throughout (see Footnote 2). In the previous example, because group members have access to at least one valid cue that discriminates within their set of information, they can always use a valid cue.

As mentioned before, this example simplifies the environments used in research on the hidden-profile effect, in which groups are usually faced with more alternatives and in particular with many more pieces of information. Nevertheless, the example demonstrates two fundamental properties of the decision strategies. First, in the majority of cases, MIN would fail to detect the hidden profile whereas TTB would detect it. Second, if individual group members' percentages of hidden-profile detections are below chance, groups that apply the majority rule will perform even worse than the individual group members do on average. In contrast, if individual group members' percentages of detections are above chance, groups will benefit from applying the majority rule – as we will see below. This pattern fits with the general finding in research on group decision making that the individual tendency to be correct or wrong is accentuated by the majority rule (see Hinsz et al., 1997; Reimer, Bornstein, & Opwis, 2005; Reimer & Katsikopoulos, 2004; Sorkin, Hays, & West, 2001).

## Generation of Environments

We now turn to the procedure we used to generate the environments in which the strategies described above were tested. There are at least two ways to produce hidden-profile environments. First, using the principle underlying hidden profiles one can systematically create environments with various numbers of cues, alternatives, and group members (e.g., Stasser et al., 1989; for a simple example, see our Table 1). Second, for a given number of cues, alternatives, and group members, the cue values describing the candidates can be randomly determined and randomly distributed among group members. From this set one can subsequently select all those environments containing hidden profiles. While previous research usually created hidden profiles systematically, we selected them from randomly generated samples of environments in which group members received different quantities of cue values. This enabled us not only to compare the performance of the strategies in environments with and without a hidden profile, thus testing their robustness across different information environments, but also to explore the effect of the quantity of shared cue values, which is assumed to be the most crucial factor with respect to group performance in hidden-profile environments (e.g., Wittenbaum & Stasser, 1996).

Specifically, we created environments in which three

candidates were described on 20 dichotomous cues. To have a reasonable number of hidden-profile environments, we generated 300,000 distributions of information by randomly assigning each of the three candidates a positive or a negative value on each of the 20 cues, which amounts to  $2^{60}$  possibilities.

## Distribution of Information among Group Members

Next, the 60 cue values of each environment were distributed among the four group members. Thereby, the amount of shared information was systematically varied, with the constraints that the group as a whole always had access to all available information; that is, each cue value was known to at least one group member. In the most extreme case, in which group members shared no single cue value, each member received 15 (25%) of the 60 cue values. This number was systematically increased in 10 steps by adding 5 cue values per step, yielding conditions in which each member had information about 20, 25, 30, ..., 60 cue values. Unknown cue values were coded as a "0"; that is, when UWM was applied these values were irrelevant, and when MIN or TTB were applied these values led to discrimination if they were compared with a positive or a negative value.

In the conditions in which none of the group members were "omniscient," the 60 pieces of information were first randomly distributed among the four group members under the restriction that group members were not allowed to receive more pieces of information than specified in the respective conditions. This step guaranteed that every cue value was known by at least one group member. Then, each simulated group member filled up her set by randomly choosing additional cue values she did not already possess, except for the condition in which each individual received only 15 pieces of information. Overall, there were 30,000 distributions of information on each percentage of shared information.

When comparing the hidden-profile environment displayed in Table 1 with those that can result from randomly filling in a matrix of 3 candidates by 20 cues and distributing this information among group members, one can become aware of a distinction that has so far been overlooked in research on hidden profiles. In the example given in Table 1, the group knows that Candidate A has positive values on Cues 1–3, and Candidate B has positive values on Cues 4–7. However, the group has no knowledge about Candidate B's values on Cues 1–3 and on Candidate A's values on Cues 4–7. As a consequence, group members share a cue only if they also share a cue value. This is not the case in our simulations. Imagine, for instance, that Member 1 knows Candidate A has a positive value on Cue

18 but has no information about the value of Candidate B on this cue. Further imagine the opposite is true for Member 2, who knows B's value on Cue 18, but not that of A. Thus, unlike in Table 1, in our simulations cues can be shared even if the values on those cues are unshared.<sup>3</sup>

## Results

Before we turn to the question of how the strategies performed depending on the distribution of information, we will have a closer look at those distributions.

### Characteristics of Environments

How many members of our simulated groups had access to a cue value (shared cue values) and to a cue (shared cue) averaged across all environments that we generated? As can be seen in Figure 2, the average number of shared cue values is a linear function of the number of cue values each group member had access to (see the straight line). The more cue values each individual received, the more group members, on average, shared information on a particular cue value. For example, if each group member had access to 50% of the cue values, each value was, on average, shared by two group members. The broken line in Figure 2 shows the average number of group members who shared a particular cue. As can be seen, sometimes group members shared a cue without sharing a particular value on that cue: Even in the condition in which each of the four group members had only 15 cue values and thus all cue values were unshared, each cue was, on average, shared by at least two group members.

<sup>3</sup> Usually only the overall amount of shared and unshared information is reported in research on the hidden-profile effect, without mention of whether the unshared information is based on identical or on different cues. However, that the choice alternatives are described by exclusive sets of cues can sometimes be derived from the descriptions of the materials, e.g., on how the cues were selected with regard to their valence. Moreover, in his simulation of the DISCUSS model, Stasser (1992) appended a matrix giving detailed information about the distribution on the level of single items. This matrix was also used in a prior, classic experiment on the hidden-profile effect conducted by Stasser and Titus (1985). As can be seen in this matrix, the alternatives were described by different sets of cues. In their studies on group decision making, Gigone and Hastie (1997) used cues on which group members knew values on different objects. However, in these studies, group members always had access to all available cue values if they knew a cue, so that group members again shared a cue if they shared cue values.

Does the likelihood that an environment will contain a hidden profile depend on these features? Overall, 456 (of the 300,000) distributions had a hidden profile. As Figure 3 shows, the likelihood of a hidden profile is an inverse U-shaped function of the number of shared cue values. In particular, the likelihood of a hidden profile is highest if group members have access to half of the available information. Then, each cue value is, on average, shared by two group members. If all cue values are shared, a hidden profile cannot occur by definition, and if all cue values are unshared a hidden profile is also very unlikely to occur.

### Simulation 1: How Often Do the Decision Strategies Detect Hidden Profiles?

In the first simulation, we selected from the total set of distributions of information those cases that contained a hidden profile. By definition, in hidden-profile environments, the percentage of correct choices made by Omni-UWM amounts to 100%, and that achieved by Ind-UWM

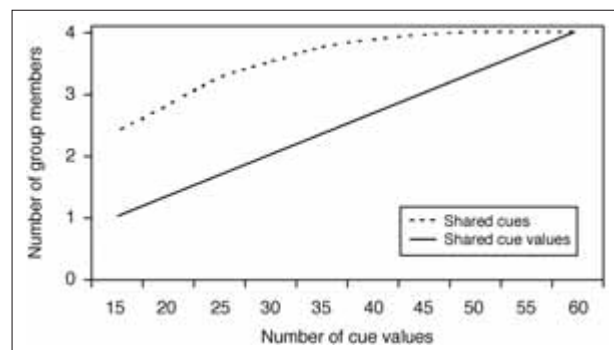


Figure 2. Number of group members who shared information on a specific cue value (shared cue value) and who shared a cue by knowing at least one value of this cue (shared cue).

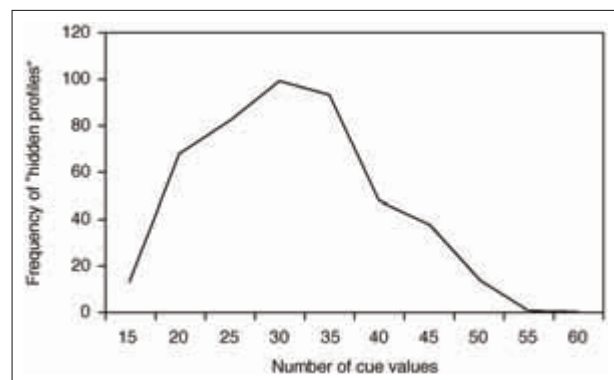


Figure 3. Absolute frequency of hidden-profile environments as a function of the number of cue values known by each group member in a set of 300,000 randomly generated distributions.

and Maj-UWM is zero. But what about the other strategies? First, as Table 2 shows, the strategies differ in their frugality, that is, in the number of cues they look up. Whereas UWM looked up all 20 cues, the much more frugal simple heuristics used, on average, a maximum of 2 cues to form a decision.

Second, the strategies also differed with respect to their performance. For each unit of analysis, search ordered by validity was superior to random search. Particularly, if the omniscient group member chose cues randomly (Omni-MIN), the percentage of correct choices was somewhat below 50%. For the individual group members who searched for cues randomly (Ind-MIN), performance was even slightly below chance level (33.3%), which was also the case if they subsequently integrated their decisions on the basis of a majority rule (Maj-MIN). In contrast, the communication-based Minimalist (Com-MIN) was much more likely to detect the best candidate even though that candidate's profile was hidden – the performance of this strategy was only five percentage points below that of Omni-MIN. In this situation, in which cues are very likely to be shared by more than two group members (see Figure 2), Com-MIN allows group members to make use of most of the available cue values, even if most values are unshared.

If an individual had access to all available cue values and looked up the cues according to their validity (Omni-TTB), the hidden profiles were almost always detected. Individuals who adopted this search rule (Ind-TTB) but

did not have perfect knowledge about all cue values chose the best candidate in 83.2% of the cases. Because the individuals detected hidden profiles more often than expected by chance, the majority rule (Maj-TTB) enhanced the performance of Ind-TTB, specifically, by another seven percentage points. Once again, Com-TTB reached the same performance as Omni-TTB.

Are these results affected by the number of shared cue values? In Table 3, the nine classes of the number of shared cue values in which a hidden profile could occur were split into three categories of high, medium, and low quantities of shared cue values. Because performance of UWM is always the same in the case of a hidden profile (100% accuracy of Omni- and Com-UWM, and 0% accuracy of Ind- and Maj-UWM), results are only reported for MIN and TTB. If cues are chosen randomly, the number of shared cue values has almost no effect on performance, except in the condition Com-MIN, in which the accuracy is somewhat lower when group members know a high percentage of cue values (36%) than when they know a medium (44%) or low (42%) percentage.

As seen above, Com-TTB almost always detects the hidden profiles. Conversely, Ind-TTB performs somewhat worse if group members have little information available because this enhances the likelihood that an individual will have no information on a valid cue at all and therefore has to decide on the basis of less valid cues. However, because the individuals find the best candidate in at least 80% of the cases, a percentage far above chance, integrating the individual decisions by a majority rule further enhances the number of hidden-profile detections (89%).

The results of the first simulation can be summarized as follows: Even a simple, frugal communication-based heuristic that randomly draws cues (Com-MIN) chose the best candidate in 42% of cases. Interestingly, in these hidden-profile environments, in which the distribution of information is biased such that most information held by the individual group members does not point to the best candidate, accuracy is somewhat lower if each group member knows a high proportion of cue values. Moreover, if the simulated groups have knowledge about the order of cue validities (TTB), the correct choice is made in the vast majority of cases.

## Simulation 2: Is Performance across All Randomly Generated Environments Affected by the Quantity of Shared Information?

The second and third simulations were based on representative samples of the generated environments, regardless of whether they contained a hidden profile. The purpose

Table 2  
*The Decision Strategies' Frugality and Performance in Hidden-Profile Environments, Averaged across Different Amounts of Shared Cue Values*

Decision strategy	Unit of analysis			
	Individual	Group		
	Omni	Ind	Maj	Com
	Frugality			
UWM	20	20	20	20
MIN	2.3	1.9	1.9	2.2
TTB	1.6	1.7	1.7	1.9
	Performance (in %) in hidden-profile environments			
UWM	100	0	0	100
MIN	47.1	32.0	30.5	42.1
TTB	99.8	83.2	89.9	99.8

*Note.* Omni: omniscient individual; Ind: individual group member; Maj: majority rule; Com: communication-based strategy; UWM: unit weight model; MIN: Minimalist heuristic; TTB: Take The Best heuristic; Frugality: average number of cues looked up (maximum is 20); Performance: percentage of environments in which the best candidate was chosen by the strategy from those environments that contained a hidden profile.

of these simulations was to see whether the simple heuristics' performance can be generalized to environments that are not restricted to hidden profiles (Simulation 2), and to test to what extent performance is affected by the quality of shared information (Simulation 3). The only constraint was that Omni-UWM had to yield an unequivocal decision throughout; that is, we excluded distributions in which the two or three best candidates had the same sum score. From this set, we randomly selected 1,000 environments for each of the 10 quantities of shared cue values.

Table 4 shows how often the strategies made the correct choice depending on the different percentages of cue values the group members had available. More specifically, the table shows the percentage of correct choices (a) when each group member had access to all information (60 cue values; 100%); (b) when each group member had access to half of the information (30 cue values; 50%); (c) when all information was unshared (15 cue values per

group member; 25%); and (d) across all nine cases in which group members only had access to a partial set of information (15–55 cue values; 25–92%). Because the conditions Omni and Ind are identical when individuals have access to all available pieces of information and because the performance of the strategies in the Omni condition does not depend on the quantity of shared cue values, the results in the Omni condition are not shown in the table.

As is evident from Table 4, the more cue values group members have available, the better the performances of the strategies tend to be. This holds both for the average individual (Ind), as well as for the group as the unit of analysis (Maj). However, the effect of quantity of information is different for the different strategies. There were pronounced differences with respect to performance if UWM is used. The largest differences between the 60-cue-value condition and the 15-cue-value condition are 45%

Table 3  
Average Performance (in %) of the Strategies, Separately for Low, Medium, and High Amounts of Shared Cue Values

Decision strategy	Number of members' cue values	Unit of analysis			
		Individual		Group	
		Omni	Ind	Maj	Com
MIN	High (45, 50, 55)	45.3	33.5	28.3	35.8
	Medium (30, 35, 40)	45.8	31.3	30.4	43.8
	Low (15, 20, 25)	49.7	32.7	31.3	41.7
TTB	High (45, 50, 55)	100	87.7	96.2	100
	Medium (30, 35, 40)	99.6	84.4	89.2	99.6
	Low (15, 20, 25)	100	80.1	89.0	100

Note. Omni: omniscient individual; Ind: individual group member; Maj: majority rule; Com: communication-based strategy; MIN: Minimalist heuristic; TTB: Take The Best heuristic.

Table 4  
Average Performance (in %) of the Strategies in a Representative Sample of Environments, According to Quantity of Shared Information

Decision strategy	Number (and percentage) of members' cue values	Unit of analysis		
		Ind	Maj	Com
UWM	60 (100%)	100	100	100
	15-55 (25-92%)	73.2	84.3	100
	30 (50%)	68.4	80.4	100
	15 (25%)	55.4	74.0	100
MIN	60 (100%)	51.0	59.4	53.8
	15-55 (25-92%)	44.1	49.8	50.0
	30 (50%)	43.1	48.0	53.2
	15 (25%)	41.4	45.7	51.2
TTB	60 (100%)	100	100	99.8
	15-55 (25-92%)	85.5	92.7	99.4
	30 (50%)	81.9	89.0	99.7
	15 (25%)	79.3	89.2	98.7

Note. Ind: individual group member; Maj: majority rule; Com: communication-based strategy; UWM: unit weight model; MIN: Minimalist heuristic; TTB: Take The Best heuristic.

and 26% for Ind-UWM and Maj-UWM, respectively. In contrast, the performance of TTB was far less affected by the amount of shared information. Here, the largest differences are 21% and 11% for Ind-TTB and Maj-TTB, respectively. If groups use a communication-based decision strategy, the quantity of shared information has almost no impact on performance, irrespective of whether cues are drawn randomly (MIN) or according to their validities (TTB).

Comparing the strategies' performances in the first and the second simulation allows us to determine if there is anything special about hidden-profile environments (see Tables 2 and 4). In fact, the performance of UWM differs extremely: 0% (Ind-UWM) and 0% (Maj-UWM) in hidden-profile environments (by definition) versus 73.2% (Ind-UWM) and 84.3% (Maj-UWM) in a representative sample of all randomly generated environments (see the average across the conditions 15–55 cue values in Table 4). This huge difference is due to the hidden profile being defined as a mismatch between Ind-UWM and Omni-UWM.

Can such a difference also be observed for the simple heuristics? The answer depends on whether MIN or TTB is considered. MIN finds the best candidate in hidden-profile environments (32%, 31%, and 42%, for Ind-MIN, Maj-MIN, and Com-MIN, respectively) less often than in a representative set of environments (44%, 50%, and 50%, respectively). In contrast, TTB is barely affected by this variation and instead chooses correctly in the vast majority of environments, be it within the hidden-profile environments (Table 2) or within those from the representative set (Table 4).

### Simulation 3: Is Performance across All Randomly Generated Environments Affected by the Quality of Shared Information?

In the simulations reported above, the group members' cue validities matched, on average, the cue validities in the

Omni-condition. To see what happens if this match is systematically distorted, we ran another set of simulations, in which cue values were distributed in a biased way such that the values either on the 10 most valid or on the 10 least valid cues had a higher chance of being shared. Our intuition was that the effect of the quality of the shared information should be even more pronounced than that of the quantity of shared cues and cue values (see Reimer & Hoffrage, 2003).

In Simulation 3, the available cue values were first randomly distributed among group members as before. Then, each group member filled up her set of known cue values to 50% by randomly choosing additional values, from the set of either the 10 most or the 10 least valid cues. As can be seen in Table 5, there was an interaction between strategy and quality of information; that is, the effect of this variation depended on the strategy. It was smallest for TTB: The performance of Ind-TTB was only 10 percentage points higher if the shared information was systematically biased toward the more valid cues. This difference was further diminished when the individual decisions were integrated by a majority rule (Maj-TTB). Note that even if Ind-TTB was handicapped through a systematic bias toward values of the least valid cues being more prevalent in the group, it still achieved a performance of 79%.

Com-TTB is not much affected by this variation but chooses correctly in almost all of the cases. This holds even in the condition in which the least valid cues are more often shared and group members know fewer values on the most valid cues: As long as they have any information on the most valid cues, performance is not impaired. The difference with respect to performance in the MIN-conditions is about 20% (30% for Maj-MIN). The variation most strongly affects the performance of UWM: The performance of Ind-UWM and Maj-UWM drops dramatically if group members share more values on less valid cues, which results in a difference of about 67 percentage points. In line with the accentuation assumption (see Reimer, 2001), this difference is again enhanced if the individual decisions are integrated by a majority rule.

Table 5

*The Decision Strategies' Average Performance (in %) According to the Unit of Analysis (Ind, Maj, and Com) and whether Cue Values on the 10 Most or the 10 Least Valid Cues Had a Higher Chance of Being Shared*

	Ind		Maj		Com	
	Most valid cues	Least valid cues	Most valid cues	Least valid cues	Most valid cues	Least valid cues
UWM	92.5	25.2	97.9	21.4	100	100
MIN	54.0	33.9	65.2	34.2	58.9	37.8
TTB	89.1	79.1	95.3	90.4	99.7	98.7

*Note.* Ind: individual group member; Maj: majority rule; Com: communication-based strategy; UWM: unit weight model; MIN: Minimalist heuristic; TTB: Take The Best heuristic.

## Discussion

Recent developments in research on individual decision making led to a specification of several simple heuristics that perform astonishingly well when compared to more complex decision strategies (Gigerenzer et al., 1999). In the present paper we adapted some of these heuristics to group decision making within the hidden-profile paradigm and explored the performance of these heuristics in a series of Monte-Carlo studies in which four group members had to choose one of three candidates for a position. As a standard of comparison we used a unit weight linear model (Stasser & Titus, 1985, 1987). In the remainder of the paper we will summarize the main findings, discuss the prescriptive implications of the present work, and derive questions for further research.

### Major Findings from the Simple Group-Heuristics Approach

How do the decision strategies perform in different environments in which the alternative with the highest overall sum score serves as the gold standard? First, in line with previous research (Davis, 1973; Hinsz et al., 1997; Reimer, 2001), the simulations replicated the finding that decisions based on the majority rule accentuate the averaged individual decisions: If individuals' performances were above chance, Maj-UWM performed better than Ind-UWM, and if the individuals' performances were below chance, Maj-UWM performed even worse.

Does performance of the decision strategies depend on whether there is a hidden profile in an environment? While this was the case for Maj-UWM, the performances of MIN and, in particular, of TTB were less strongly affected by this variation, as revealed through a comparison between Simulations 1 and 2.

How is the performance of the strategies affected by the quantity of shared cues and shared cue values? When the group used a communication-based strategy, shared cues had a stronger impact on group decisions than unshared cues because each group member was more likely to choose shared cues than unshared cues. Recall that according to the communication-based heuristics as they were implemented in the simulations, group members chose from the cues for which they knew the value for at least one candidate. As a consequence, the number of values shared on a cue was irrelevant as long as group members had any information on a cue. In particular, the communication-based heuristics performed very well across the different environments. In at least 98% of the cases, Com-TTB made the correct choice, even though this heuristic is much more frugal and faster than the majority-based decision strategies, which additionally require

that group members form an individual decision first. If individuals did not have access to all information, Com-TTB outperformed the majority-based lexicographic heuristics (Ind-TTB and Maj-TTB). This is because lack of knowledge may prevent individuals from using the most valid cues.

How is the performance of the strategies affected by the quality of shared cues and shared cue values? Again, the number of shared cue values did not affect TTB if group members had any knowledge on the valid cues at all, as revealed by Simulation 3.

### Should Groups Use Simple Heuristics?

The robust empirical finding that groups fail to detect hidden profiles (Stasser & Titus, 1985; Wittenbaum & Stasser, 1996) does not necessarily imply that an exhaustive information search and exchange is a prerequisite for good group decisions. In fact, our simulations have shown that a communication-based lexicographic strategy provides a powerful tool for making fast and frugal group decisions and thus also deserves further attention from a prescriptive point of view. This conclusion is consistent with findings in individual decision making showing that frugal non-compensatory heuristics yield surprisingly good performance when compared to compensatory strategies that combine all available information. When cross-validated, these simple heuristics often even outperform more complex strategies (Czerlinski et al., 1999; Martignon & Hoffrage, 2002). The more complex a strategy is, the more likely it is to overfit the existing data and to drop in performance when generalized to new data. Thus, when making out-of-sample predictions, simple heuristics perform as well as they do not in spite of, but because of their simplicity.

Note that in the present simulations, we defined validity with respect to each environment, that is, within each triplet of candidates, and subsequently computed the performance of the strategies within this environment. This certainly explains the good performance of TTB, because in many cases this heuristic could rely on a cue with a validity of 1, whereas MIN had a higher chance of using a cue with a validity of .5 or even 0. Even UWM performed worse than TTB (see Table 4) because this strategy also uses information on less valid cues, thereby weakening the impact of the information on the highly valid cues. Thus, in terms of validity, if group members have knowledge about the rank order of cues, TTB might be a good group strategy. This holds in particular if the distribution of cue validities is highly skewed (see Reimer & Hoffrage, 2003).

The superiority of TTB is not restricted to the present simulations. Its success was also seen in another series of simulations in which we used an outside criterion (Reimer

& Hoffrage, 2003). Moreover, in those simulations an environment consisted not of 3 candidates, but of 20 candidates, and validity was not computed within a triplet of candidates, but across all 1140 possible triplets that could be generated from the set of 20 candidates. In those simulations we systematically varied the distribution of validities. We found an interaction between strategies' performance and the distribution of the cues' validities: If the validities followed a linear distribution, UWM was the best strategy, and if they followed a J-shaped distribution with a few highly valid and a large majority of substantially less valid cues, TTB was the best strategy. This demonstrates that the prescriptive question of which strategy should be used cannot be answered without taking the structure of information in the task environment into account (see also Simon, 1956).

## Open Questions and Future Directions

The repertoire of heuristics available to a given species at a given point in its evolution has been called its "adaptive toolbox" (Gigerenzer & Selten, 2001). An interesting question is which features of the task or which environmental conditions trigger which strategy an organism might select from its toolbox to solve a particular task at hand. The current approach considered simple group heuristics for both the communication-based and combination-based ways a group can reach a joint decision. When do groups use a communication-based strategy and when do they use a combination-based one? This question has been extensively discussed in the literature on group decision making. In fact, several task characteristics that may moderate to what extent a group's decision is influenced by communication have been identified (see Hinsz et al., 1997). Yet, as Baron et al. (1992, p. 106) remarked, "it would be nice if one of the approaches alone provided a complete understanding of how groups reach their decisions but this is not the case."

Following up on our distinction between shared cue values and shared cues, we submit that it is interesting to study whether groups are more likely to use a communication-based strategy if the individuals have incomplete information. Having access to several or even all values of a cue might enhance the likelihood that group members will enter the group discussion with strong opinions about what would be the correct decision, whereas group members with little knowledge may prefer to search for more information by discussion. Thus, a communication-based strategy may be fostered by a situation in which group members are told or realize that they have unshared information. Somewhat counter-intuitively, telling a group that this is the case does not enhance the likelihood that unshared information will be pooled during discussion

(Stasser et al., 1995). However, it is not clear from this research whether groups exchange more information on shared cues or on shared cue values.

This also points to the more general question that deserves to be tested empirically, namely, whether shared cues or shared cue values have a sampling advantage during discussion. For example, if groups use one of the simple communication-based decision strategies one would expect group members to exchange more cue values on a shared cue than on an unshared cue because shared compared to unshared cues should have a higher likelihood of being drawn by a group (sampling advantage of shared cues).

In addition, another aspect of the communication-based approach is interesting from the present viewpoint of simple group heuristics. By mentioning that a candidate has a specific cue value, a group member communicates not only this specific cue value of the candidate but also that this cue is worth consideration. The question then arises: Which group members bring their information to the group's attention? Studies on the hidden-profile effect have shown how (perceived) status and expertise can influence information processing. These studies revealed that the sampling advantage of shared information can also be observed in teams that consist of experts (e.g., Larson, Christensen, Abbott, & Franz, 1996; Larson, Christensen, Franz, & Abbott, 1998). However, whereas low-status group members in particular are likely to mention shared information more often than unshared information (Wittenbaum, 1998), group members who are high in expertise are more likely to repeat unshared information (Larson et al., 1996). Further, unshared pieces of information are also considered to be more important and are recalled better when they are mentioned by members who are high in status (Wittenbaum, 2000; Wittenbaum & Stasser, 1996).

When using one of the communication-based strategies, the groups in our simulations randomly picked a member, which may be reasonable if members do not differ systematically in status, expertise, or on other dimensions that may have an influence on participation in communication. In real groups, however, in which such differences exist, it is likely that high-status group members are more influential on the selection of cues for cue-wise comparison than low-status group members. If status is based on – or at least correlated with – expertise, this may help groups to identify the most valid cues and to apply a lexicographic heuristic like TTB. In contrast, if status is not based on expertise, groups may exchange relatively more information on less valid cues which, in turn, may diminish their performance.

Are groups able to apply a lexicographic decision strategy like TTB? First, recall that unlike in the environments

used here, in research on the hidden-profile effect, alternatives are described by “unique cues”; that is, the group knows the value of one alternative for each cue. However, it may be the case that groups, like individuals (see Burke, 1990), are more likely to apply a cue-based strategy when they can compare different alternatives on the same cues. Second, research on individual decision making has identified conditions that foster the use of simple heuristics. Rieskamp and Hoffrage (1999) showed that under high time pressure, the best strategy for modeling choices was TTB, whereas under low time pressure, Weighted Pros (Huber, 1980) was best suited – in terms of complexity, Weighted Pros can be located between TTB and UWM. Similarly, Bröder (2000) showed that decisions could best be modeled with a simple lexicographic strategy when search for information was costly, whereas in a condition in which information was free, a linear compensatory strategy reached a higher fit. This research, together with the present simulation results, leads to the interesting and counterintuitive prediction that hidden profiles may be detected more often when information is costly for group members.

The simulations revealed that the likelihood that an information environment contains a hidden profile is very low if cue values are randomly assigned to the candidates and are randomly distributed among group members – at least for the number of candidates, cues, and group size we have chosen. However, this does not necessarily mean that hidden profiles are equally rare in everyday life, although this is probably the case for those environments in which the choice alternatives are described by exclusive sets of cues. We agree with Winquist and Larson (1998) that it would be interesting to know how often hidden profiles occur in natural field settings. As suggested by an ecological approach to cognition, decision strategies of real groups may well be adapted to the structure of information in such settings. For instance, exchanging shared information may simply reflect that group members agree on what the important cues are. Moreover, in a world of uncertainty in which some information may be wrong, communicating shared information can serve the purpose of validating information (Parks & Cowlin, 1996). Real-world environments provide the ultimate test for both the descriptive and prescriptive utility of complex strategies such as a compensatory linear model and simple group heuristics.

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