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THE ECOLOGICAL RATIONALITY OF SIMPLE GROUP HEURISTICS: EFFECTS OF GROUP MEMBER STRATEGIES ON DECISION ACCURACY

ABSTRACT. The notion of ecological rationality implies that the accuracy of a decision strategy depends on features of the information environment in which it is tested. We demonstrate that the performance of a group may be strongly affected by the decision strategies used by its individual members and specify how this effect is moderated by environmental features. Specifically, in a set of simulation studies, we systematically compared four decision strategies used by the individual group members: two linear, compensatory decision strategies and two simple, noncompensatory heuristics. Individual decisions were aggregated by using a majority rule. To assess the ecological rationality of the strategies, we varied (a) the distribution of cue validities, (b) the quantity, and (c) the quality of shared information. Group performance strongly depended on the distribution of cue validities. When validities were linearly distributed, groups using a compensatory strategy achieved the highest accuracy. Conversely, when cue validities followed a J-shaped distribution, groups using a simple lexicographic heuristic performed best. While these effects were robust across different quantities of shared information, the quality of shared information exerted stronger effects on group performance. Consequences for prescriptive theories on group decision making are discussed.

KEY WORDS: compensatory and noncompensatory decision strategies, group decision making, group performance, simple heuristics

1. BOUNDED AND ECOLOGICAL RATIONALITY IN GROUP DECISION MAKING

The accuracy of group decisions often depends on two fundamental dimensions: on features of the available information and on how this information is processed by group members and integrated into a group decision. This paper is about the match between these two dimensions. In a series of simulation studies, we explored whether group performance depends on (a) the decision strategy used by individual group members, on (b) features of the information environment, in which these strategies may be used, and on (c) the ecological rationality of the decision strategies, that is, their fit with specific features of the information environment. Which decision strategy works best in which information environment? When is it beneficial to consider all of the available information? When is it beneficial to take the predictive validity of the information into account? To address these issues we have chosen a classic task from an established research tradition in group decision making (Davis, 1973; Stasser, 1992; Stasser and Titus, 1985): a four-member personnel committee has to select one of three candidates who are applying for a position.

What strategy could a group member use to process the information that is available about the candidates, and which strategies are capable of identifying the best-suited candidate? In this study, we focus on whether good group performance requires that group members use a compensatory decision strategy that considers all available information, or whether a noncompensatory heuristic that limits information processing could also yield comparable results. Although the idea that individual group members might use noncompensatory heuristics has been considered before (e.g., Gigone and Hastie, 1997; Stasser, 1992), this issue has not yet been systematically addressed in research on group decision making. Instead, models on group decision making usually assume that group members integrate their individual knowledge using a unit weight linear model (e.g., Stasser, 1992) or a weighted additive model (e.g., Gigone and Hastie, 1996; Stasser, 1988).

In the literature on individual decision making, however, it is well known that inferences do not necessarily improve if more information is taken into account. Moreover, it is often the case that not all relevant information will be readily available; and even when it is, the computational capacity necessary to use strategies that may be considered the normative correct ones is frequently lacking. Such constraints compel us to use heuristics that work within our cognitive boundaries, and since these boundaries are ubiquitous, Simon (1982) concludes that "bounded rationality is what psychology is all about," Recently, Gigerenzer, Todd, and the ABC Research Group (1999; see also Gigerenzer, 2005) have proposed several models of bounded rationality—a collection of simple heuristics that are easy to process (thus allowing for fast decisions) and that require little information (thus being frugal). These fast and frugal heuristics are defined in terms of simple building blocks that specify how information is sought (*search rule*), when the search for information is stopped (*stopping rule*), and how a decision is made based on the information that has been gathered (*decision rule*). They make inferences about an external criterion and thus can be either right or wrong (for a comparison between simple heuristics for inferential versus preferential choices, see Rieskamp and Hoffrage, 2005 unpublished). The two features—precise definition as a process model and the availability of an external criterion—make it possible to implement fast and frugal heuristics in computer programs and to determine their ecological rationality by assessing their accuracy in various information environments. Previous results suggest the heuristics often compete well with more complex strategies such as multiple regression, Bayesian networks, and neural networks (Gigerenzer et al., 1999; Martignon and Hoffrage, 2002). Under specific conditions, these heuristics can even outperform strategies that are more computationally demanding (Czerlinski et al., 1999; Hogarth and Karelaia, in press; Hoffrage and Reimer, 2004).

The availability of an external criterion is crucial for the present work. In research on group decision making (e.g., Stasser, 1992; Stasser and Titus, 1985) the best choice is often defined by a particular decision strategy—namely, a unit weight linear model (UWM) that sums up the cue values of each candidate and chooses the one with the highest sum score (Dawes and Corrigan, 1974). Taking UWM as the gold standard has an important consequence: group decisions cannot improve if they are based on a partial set of information or on another decision strategy. In this study, we deviated from this tradition by introducing an external criterion. Introducing an outside criterion makes it possible to compare the performance of several strategies for cue-based inferences that group members may use, where performance is measured as the proportion of choices favoring the alternative with the highest criterion value rather than the proportion of choices matching UWM's choice (for an application of simple group heuristics where UWM is maintained as a gold standard, see Reimer and Hoffrage, 2005).

In our simulations, we focused on how group performance is affected by the decision strategies that are used by individual group members. Therefore, we kept the rule that integrates the individuals' decisions into a group decision constant by using a majority/plurality rule. Because the current task has no *demonstrably* correct solution, as none of the simulated group members has access to the external criterion value of any of the candidates, real groups will most likely use a majority rule to combine members' choices (for a related argument, see Gigone and Hastie, 1997).

The second issue we focused on concerns the ecological rationality of the decision strategies, that is, their fit with specific features of the information environment: When and why do they work? According to Todd and Gigerenzer (1999), this is a central question which has not received much attention so far (for an example, see Martignon and Hoffrage, 2002). In the present work, we vary two aspects of the ecology. One is the distribution of cue validities: do all of the cues predict the criterion equally well, or, if not, how are their validities distribute? While this aspect describes a particular structure of the information that is available to the group as a whole, the other aspect that we manipulated concerns the quantity and quality of information that is distributed among the individual members. Such manipulations are motivated from research indicating that group decisions can be strongly affected by how much and which information is known by all members of a group and, therefore, shared among group members (see Stasser and Titus, 1985). In the present simulations, we varied the quantity of shared information by varying the amount of information that was known to the individual group members. The purpose was to determine for each of the decision strategies whether and to what extent a lack of individual knowledge impairs its performance (see Stasser, 1992). Moreover, we also varied the quality of shared information. Whereas the quantity of shared information has been addressed in many studies on group decision making (Wittenbaum and Stasser, 1996), the quality of shared information has not received much attention (see Gigone and Hastie, 1997). However, the question of which—as opposed to how much—information should be processed by the group might be even more critical for group performance.

Applying the framework of fast and frugal heuristics to group decision making seems to be promising for both research traditions. For the fast and frugal heuristics approach, group decision making is new territory. Conversely, research on group decision making has not yet paid much attention to decision strategies used by individual group members or to the validity of the available information (for an exception, see Gigone and Hastie, 1996, who conceptualized group decision making in the framework of the Brunswikian lens model; and Stasser, 1988, who compared a summation and averaging rule; for applications of simple group heuristics on other tasks, see Reimer and Katsikopoulos, 2004).

The paper is structured as follows: first, we introduce the task that was used in our simulations and the strategies that might solve this task. Second, we describe the environments in which these strategies were tested and provide details on how the simulations were implemented. Third, we report the results from a series of three simulations. Specifically, we address to what extent the performance of decision strategies was affected by the distribution of cue validities in an environment (Simulation 1) and by the quantity (Simulation 2) and quality (Simulation 3) of shared information, In the concluding discussion, future research issues on group decision making are presented.

2. THE TASK

The simulated groups were given a classic task (cf. Davis, 1973; Stasser and Titus, 1985): a four-member personnel committee has to decide which of three candidates is best suited for a position. Because we were interested in studying the ecological rationality of different decision strategies, we constructed a reference class and introduced an outside criterion by assigning candidates different values on a criterion (i.e., suitability for the job). The reference class from which the three candidates were drawn consisted of 20 potential job applicants. We assigned job applicants different criterion values such that they could be unequivocally rank ordered according to the criterion (see Table I; without loss of generality, $A > B > C > \cdots > T$; for the concept of a reference class (see Gigerenzer et al., 1991).

Thus, in this environment, there is a correct decision for every potential triplet of candidates with which the group may be faced. If presented with the triplet B, C, and E, for example,

TABLE I

The reference class: The 20 candidates are rank ordered according to an external criterion and are described by 20 dichotomous cues that are positively related to the criterion

Candidate	Criterion	Cues						
		1	2	3	4	5	…	20
A	20	1	1	−1	1	1	…	−1
B	19	1	1	1	−1	1	…	1
C	18	1	−1	1	−1	−1	…	−1
D	17	−1	1	1	1	1	…	−1
E	16	1	1	−1	1	−1	…	−1
…	…	…	…	…	…	…	…	…
T	1	1	−1	−1	−1	…	1	

the correct decision would be B because Candidate B has the highest criterion value. Group members did not know the criterion values but had information on 20 dichotomous cues. Cue values were '+1' or '−1' and were coded such that the cues were positively correlated with the criterion, that is, a positive cue value indicated a higher qualification than a negative cue value did. In other words, group members were assumed to know if a cue speaks in favor or against the suitability of a candidate. Note that the positive correlation held across all 20 candidates, but not necessarily for any given triplet.

3. THE DECISION STRATEGIES

The decision procedure was as follows: each simulated group member had access to a certain amount of information on the three candidates, who were drawn from the reference class. Unknown cue values were treated as a '0', group members did not have contradictory information, and the group as a whole always possessed the entire set of information because each cue value was known by at least one group member. On the basis of their individual knowledge, the group members first formed an individual decision. Subsequently, the group integrated the individual decisions into one group decision. We next turn to the question of how the group members could reach their decision based on their individual information. Subsequently, we describe how the group integrated individual decisions into one group decision.

3.1. *Decision strategies for individuals*

For the present task, group members have a wide range of strategies at their disposal (for a selected sample, see Rieskamp and Hoffrage, 1999). Here we focus on two standard benchmark-strategies and two limited-information heuristics: (1) the UWM, a linear model that selects the candidate with the highest sum score, (2) the *Weighted Additive Model* (WADD), a linear model that sums up weighted cue values and selects the candidate with the highest score, (3) the *Minimalist* heuristic (MIN), which compares candidates on the basis of randomly chosen cues, and (4) the *Take The Best* heuristic (TTB) that looks up cue values in an order established by cue validity.

Gigone and Hastie (1997) have proposed a general model on individual and group decision making that can be adapted to represent the four decision strategies. Consider the simplest case, in which an individual group member A has to choose between two alternatives. Member *A*'s individual inference or opinion O_A can be described with a weighted additive model of the cue value differences

$$O_A = \sum_{i=1 \ldots m \leqslant k} w_i (c_{1i} - c_{2i}) + e. \tag{1}$$

The i subscripts a subset of the k cues (in our case, $k = 20$), and m denotes how many cues are considered (with $m \leqslant k$). The values of Alternatives 1 and 2 on cue i are described by c_{1i} and c_{2i}; w_i is the weight of the respective cue, which is assumed to be identical for all alternatives; and e is an unmodeled error. Thus, individual group member inferences or opinions are modeled as a sum of weighted cue value differences. If the sum score O_A is positive, Alternative 1 will be chosen, if this sum score is negative, Alternative 2 will be chosen. If the difference is zero, the decision strategy does not allow for an unequivocal decision and both alternatives remain in the choice set.

In our task, group members had to choose among three candidates. The model can be extended to a choice set that comprises more than two alternatives by a procedure that compares alternatives pair-wise and excludes alternatives from the choice set by applying equation (1). At the start, all alternatives are in the choice set. Alternatives that are not chosen in a pair comparison are consecutively excluded. The procedure stops when only one object remains or when all remaining objects in the choice set have equal scores. In the latter case, one of the remaining alternatives is randomly chosen. Note that the order in which alternatives are compared does not affect the final decision in our task and, therefore, with which pair the procedure starts is inconsequential for our purposes. In our case of three alternatives. Candidates 1 and 2 may be compared first. The candidate with the smaller score will be excluded from the choice set and the candidate with the larger score will be compared with the third candidate. The major difference between the four decision strategies consists in how they determine the candidates' scores—in whether and how they weight cue differences (w) and in whether they consider all or only a partial set of cues (m).

Unit Weight Model (UWM). As is indicated by its name, the UWM weights all cues equally (thus, $w = 1$) and considers all available cue values (thus, $m = k$). Dawes (1979) demonstrated that in cross-validation such a simple linear model with unit weights can perform astonishingly well when compared to multiple regression with its complex procedure for calculating the weights. The UWM has since been used as a model for both individual (e.g., Bröder, 2000; Rieskamp and Hoffrage, 1999) and group decision making (e.g., Stasser and Titus, 1985).

Weighted Additive Model (WADD). Like UWM, WADD combines cue values by adding them up, except that they are not equally weighted but weighted by Goodman-Kruskal validities (see Martignon and Hoffrage, 2002). Specifically, the weight used by WADD is

$$g = 2\nu - 1, \tag{2}$$

where g is the Goodman-Kruskal validity of a cue. Following Gigerenzer et al. (1991), ν is the cue validity and is defined by

$$\nu = R/(R + W), \tag{3}$$

where R is the number of correct inferences, and W the number of wrong inferences based on that cue alone. In other words, the validity ν of a cue is the proportion of correct inferences in the set of all pairs in which the cue discriminates between two alternatives (for other definitions, see Martignon and Hoffrage, 2002). Because the cue values of '+1' and '−1' were coded such that the cues were positively correlated with the criterion, all cues had $v \geqslant 0.5$.[1]

Payne et al. (1993) and many others have used weighted additive strategies as a norm to which participants' choices have been compared. While UWM and WADD are compensatory strategies in which positive cue values for some cues can be compensated for and thus possibly overruled by negative cue values for other cues (and vice versa), this is not the case for the MIN and the TTB. These frugal heuristics eliminate candidates on the basis of limited information, comparable to Tversky's Elimination By Aspect (EBA) strategy for preferential choice. The EBA selects cues with probabilities proportional to their weights. The MIN and TTB differ from EBA in that Min treats all cues equally by randomly drawing cues and TTB looks up cues in a deterministic order according to their validities.

Minimalist (MIN). Although UWM is simple, it is not frugal because it uses all available information. The MIN, by contrast, requires no cue value combining and is more frugal because it stops the information search as soon as it finds one cue that discriminates between the alternatives (i.e., $1 \leqslant m \leqslant k$). In the case of two alternatives, 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 the two candidates.
- *Stopping rule*: If the two objects have different values on this cue and if the cue thus discriminates or if all cues have been looked up already, then stop search and proceed with the next step; otherwise search for another cue.
- *Individual decision rule*: Predict that the candidate with the higher cue value has the higher criterion value. If both candidates have identical values and search cannot be continued because all cues have already been looked up, then choose randomly among the two candidates.

The MIN was proposed by Czerlinski et al. (1999). The name indicates that this cue-based heuristic requires minimal knowledge. All that is required is knowledge about the direction of each cue, that is, whether a candidate with a higher cue value is more likely to have the higher or the lower criterion value. We extend MIN to more than two alternatives by excluding those candidates from the choice set that do not have the highest value along the chosen cue.

Take The Best (TTB). If a decision maker has an idea about the validity of the cues, he or she may follow MIN's algorithm but draw the cues in an order established by their (perceived) validity rather than randomly. The TTB first compares the three candidates on the basis of the most valid cue. If the most valid cue discriminates by allowing an unequivocal decision, no further information is considered and the candidate with the highest value is chosen. If two candidates share the highest cue value, the third competitor is excluded from the choice set, and competition among these two continues by considering the next-most-valid cue, and so on.

The four decision strategies vary on two dimensions: (1) Whereas UWM and WADD require exhaustive information processing, MIN and TTB are limited-information strategies that stop information processing as soon as only one candidate remains in the choice set (exhaustive versus limited information processing). Moreover, UWM and WADD are compensatory strategies in which positive values on some cues can be compensated for and overruled by negative values on other cues and vice versa. This is not the case for the two noncompensatory heuristics, MIN and TTB. (2) Whereas UWM and MIN do not require any knowledge about the validity of cues, WADD and TTB take cue validities into account: the usage of TTB requires knowledge about the rank order of cues and WADD additionally requires that individuals know the validities. All four decision strategies describe how group members can form an individual decision. Next, we will describe how the individual decisions or opinions can be integrated into one group decision.

3.2. *Decision strategies for the integration of individual decisions into a group decision*

In the social psychological literature on group decision making, two general approaches have been proposed to model how groups integrate the in formation that is available to individual group members into a group choice (see Baron et al., 1992; for an overview see Hinsz et al., 1997). The two approaches differ in whether they predict group decisions on the basis of the information that is exchanged during discussion (social communication approach) or on the basis of the individual group member opinions (social combination approach). In addition, several mixed models have been considered that assume that pooled information may alter the individual group member opinions (e.g., Stasser, 1992). In the present simulation, we focus on a decision strategy that fits into the social combination approach. For an application of simple group heuristics that fit into the social communication approach (see Reimer and Hoffrage (2005)).

How can the group reach a decision if group members have already formed an opinion at the outset of the group decision process? Several social combination models have been proposed in the literature that may be implicitly or explicitly used by a group (Davis, 1973): groups may (1) randomly draw an alternative among those alternatives that are advocated by at least one group member (equiprobability), (2) draw alternatives with probabilities proportional to the number of group members who favor them (proportionality), (3) decide for a correct decision if it is favored by at least one group member (truth wins) or (4) use a voting rule like the majority rule (for a list of nine combination rules, see Hastie and Kameda, 2005). Research within the social combination framework has consistently shown that the predictive accuracy of these models depends on features of the task (Davis, 1973; Laughlin and Ellis, 1986; Hinsz et al., 1997). Typically, if a task has a correct solution (intellective task), which is known by at least one group member who is able to demonstrate its correctness, then group decisions can be best described by a truth-wins or truth-supported wins model (Laughlin and Ellis, 1986). In contrast, if a task has no demonstrably correct solution (judgmental task), group behavior usually can be better described by a voting rule like the majority rule. In the simulations reported below, we restricted ourselves to the majority rule, which seems to be the most reasonable model in our task. Our task may be described as a judgmental task, whose objectively correct solution is not demonstrable, since none of the group members has knowledge about the candidates' criterion values (for a comparison of different social combination rules, see Davis, 1973, 1992; Einhorn et al., 1977; Hastie and Kameda, 2005; Hinsz et al., 1997; Reimer and Katsikopoulos, 2004).

The group decision rule is thus as follows: predict that the candidate with the most votes has the highest criterion value. Following Gigone and Hastie (1997), this rule can be described by

$$G = O_M + e', \tag{4}$$

in which G is the group decision, O_M is the option favored by a majority (or plurality) of the group members, and e' is unmodeled error. In the simulations; ties were resolved by a proportionality rule. In our case of a four-member group and three alternatives, a tie can only arise when two members favor one candidate and the remaining two members favor another. candidate. In this situation, the simulated groups randomly chose one of these two candidates that were favored by two group members. So, the full rule was majority or plurality if possible, proportionality otherwise.

4. INFORMATION ENVIRONMENTS AND IMPLEMENTATION OF HEURISTICS

The notion of ecological rationality suggests that the performance of a particular strategy and hence the result of a comparison of strategies may depend on the environment in which this performance is evaluated. For example, Martignon and

Hoffrage (2002) have identified conditions favoring simple, lexicographic strategies (e.g., environments with scarce information), and conditions favoring linear models (e.g., environments with abundant information). Here we focus on another aspect of the environment, namely the distribution of cue validities.

4.1. *Structures of information in the environment*

To check for the robustness of decision strategy performance across different environments and to explore the ecological rationality of the strategies introduced above, we ran the simulations in four different types of environments. These environments were generated with a random error method, constrained such that different distributions of cue validities result (see Figure 1).[2]

In two of the four environments, the distribution of cue validities was linear (L), and in the other two they followed a J-shaped distribution (J). J-shaped distributions are ubiquitous: not only do many continuous variables (like income across individuals or number of citations of scientific papers) follow such a distribution (Hertwig et al., 1999), but the

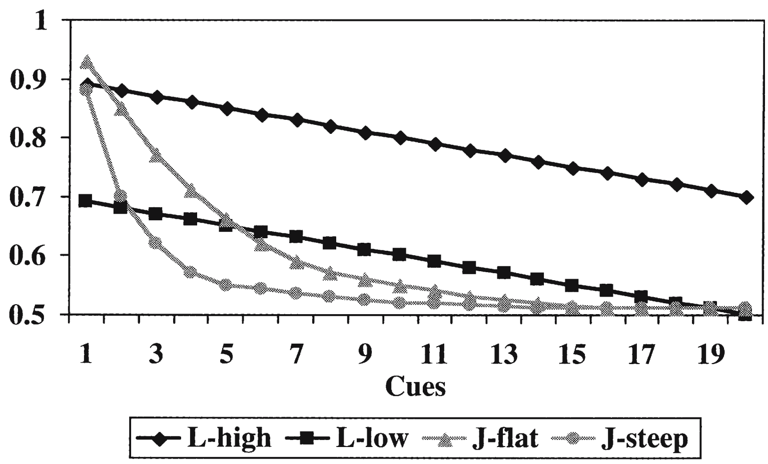

Figure 1. Distributions of cue validities. L-high, Linear cue distribution with high validities; L-low, Linear cue distribution with low validities; J-flat, Flat J-shaped cue distribution; J-steep, Steep J-shaped cue distribution.

distribution of validities of dichotomous cues in an environment also tends to be J-shaped, as our reanalysis of the environments used in Czerlinsk et al. (1999) has shown. The two linear distributions that we generated for the present simulation differ with respect to their overall means (L-high versus L-low), whereas the two J-shaped distributions differ in their skewness, which mainly affects the validity of the most valid cues (J-flat versus J-steep).

As shown in Table II, the L-high distribution has a much higher mean validity than the remaining three distributions.

TABLE II

Mean cue validities based on pairs (V_p) and triplets (V_T), correlations between the two ($r(V_p \times V_T)$), and mean correlations between cues and between candidates

	Distributions of cue validities			
	L-high	L-low	J-flat	J-steep
Validity based on pairs of candidates (V_P)				
M	0.80	0.60	0.60	0.56
SD	0.06	0.06	0.12	0.09
Validity based on triplets of candidates (V_T)				
M	0.68	0.43	0.42	0.37
SD	0.08	0.09	0.17	0.13
$r(V_p \times V_T)$	0.93	0.90	0.99	0.96
Correlations between cues				
M	0.28	0.02	0.05	0.01
SD	0.20	0.21	0.23	0.23
Correlations between candidates				
M	−0.05	−0.06	−0.06	−0.05
SD	0.22	0.22	0.24	0.22

Note. Distributions of cue validities: L-high, Linear cue distribution with high validities; L-low, Linear cue distribution with low validities; J-flat, Flat J-shaped cue distribution; J-steep,Steep J-shaped cue distribution.

Second, the L and J distributions differ from each other systematically in their standard deviations (*SDs*) according to their skewness. The validities in the L-low and the J-flat distributions have equal means, but their *SDs* differ by a factor of two. Another important feature of information environments that can affect the accuracy of decision strategies consists in the inter-correlations between cues (see Hogarth and Karelaia, in press). For example, if cues are highly correlated, information will be more redundant which may lead one to require fewer cues. We did not focus on this feature and, thus, did not systematically vary the correlation between cues. However, we checked for the cue-intercorrelations post-hoc and found that the four environments did not systematically differ with respect to the average correlations between cues. These correlations were computed as follows: in a first step, for a given pair of cues the correlation was computed across all candidates, and then, in a second step, Fishers z-transformation was used to average the correlations across all possible pairs of cues. In addition, we computed the correlation between the profiles of the candidates by a similar procedure: first, for a given pair of candidates the correlation between cues was computed, and then Fishers z-transformation was used to compute the average correlation between two candidates across all possible pairs of candidates. A high positive correlation between cues would indicate that cues are redundant. A high positive correlation between candidates would indicate that the profiles are similar. Because the values of different cues have been determined independently of each other, the correlations between the profiles of the candidates as well as the correlations between cues were on average low (see Table II).

The cue validities displayed in Figure 1 were determined on the basis of the reference class of the 20 applicants (see Table I). Because the task consisted of choosing among three candidates, we computed validities not only on the basis of all possible pairs but also on the basis of all possible triplets of candidates. The pair-wise validity of a cue, which is the usual validity measure, was determined by dividing the number of pairs in which the candidate with the higher cue value also has the higher criterion value by the number of pairs in which two candidates have different cue values. Accordingly, the triplet-wise validity was determined by dividing the number of triplets in which the candidate with the highest cue value has the highest criterion value by the number of triplets in which any candidate has a higher cue value than the remaining two candidates.

As shown in Table II the main difference between these two measures consisted in their mean values. The triplet-wise validities yielded lower means throughout. However, the cue orders established by the two different definitions turned out to be very similar, as evidenced by the fact that the correlations between the two orders were very high (at least 0.90). Consistent with this finding, we observed that the accuracy of the decision strategies and their interaction with the environmental structure was not strongly affected by the validity measure used to order cues. Thus, the major conclusions of the present paper do not depend on the validity measure and only the results based on the ordering established by the pair-wise validities will be reported hereafter.

4.2. *Implementation of heuristics in the present simulations*

For each of the four environments, all possible triplets of candidates were generated ($n = 1,140$). Then, the available information for each triplet was randomly distributed among the four group members according to the constraints of the respective condition including the distribution of cue validities and the number of shared cue values. Overall, 4,56,000 group decisions were simulated. When applying one of the validity-based decision strategies (WADD or TTB), each group member used the same set of weights (WADD) or order of cues (TTB), namely, the one based on the Goodman-Kruskal validities, which were determined on the basis of the pair-wise comparisons of all 20 candidates in the reference class.

5. PERFORMANCE: SIMULATION RESULTS

The first simulation compared the accuracy of the group decision strategies for the four distributions of cue validities when each group member knew all available information. At the same time, the first simulation served as a control condition with which the performances of the strategies in the second and third simulation were compared. The second simulation systematically varied the quantity of shared information by providing group members with a certain amount of randomly chosen cue values. Finally, the third simulation tested whether the quality of shared information determined by cue validity affected group performance.

5.1. *Does the distribution of cue validities matter?*

In Simulation 1, each group member had all of the available information, that is, all information was shared by all group members. By their very nature, the simple noncompensatory heuristics (MIN and TTB) used far fewer cues than the two compensatory decision strategies (UWM and WADD) to come to a decision. On average, the simple heuristics stopped the information search after considering three out of the 20 cues.

What price do the simple heuristics have to pay for their frugality? As Table III shows, the answer to this question depends on the environment in which performance is evaluated. We first turn to the two linear distributions. There is a substantial difference between the conditions L-high and L-low. Regardless of what strategy was used, performance was higher in the L-high than in the L-low condition. The differences between these two environments varied between 20 (WADD) and 28% (UWM) points. Furthermore, in the condition L-high, the consideration of cue validities did not substantially enhance accuracy. In contrast, in the condition L-low, the validity-based decision strategies (WADD and TTB) performed somewhat better than the respective strategies that did not take cue validities into account (UWM and

TABLE III

Accuracy of four group decision strategies (i.e., percentage of correct inferences) for different quantities of shared information and in four types of environments with different distributions of cue validities. The numbers in parentheses are the averages of individual group members' inferences

Decision strategy	Number (percentage) of members' cue values	Distributions of cue validities			
		L-high	L-low	J-flat	J-steep
UWM	60 (100%)	89 (88)	61(60)	55 (55)	46 (46)
	15–55 (25–92%)	85 (81)	59 (56)	53 (53)	45 (43)
	30 (50%)	85 (80)	58 (55)	53 (50)	45 (42)
	15 (25%)	82 (72)	57 (50)	51 (46)	43 (40)
WADD	60 (100%)	90 (90)	70 (70)	71 (71)	59 (59)
	15–55 (25–92%)	85 (81)	67 (62)	69 (65)	58 (55)
	30 (50%)	84 (80)	66 (60)	68 (64)	58 (55)
	15 (25%)	82 (72)	63 (53)	65 (57)	55 (48)
MIN	60 (100%)	77 (70)	51 (46)	47 (43)	39 (38)
	15–55 (25–92%)	66 (57)	45 (41)	42 (40)	38 (36)
	30 (50%)	64 (55)	45 (41)	42 (40)	37 (36)
	15 (25%)	62 (53)	43 (40)	42 (39)	37 (36)
TTB	60 (100%)	78 (78)	56 (56)	73 (73)	61 (61)
	15–55 (25–92%)	68 (63)	52 (49)	69 (64)	60 (56)
	30 (50%)	65 (61)	51 (49)	67 (62)	60 (56)
	15 (25%)	68 (59)	54 (47)	66 (56)	56 (49)

Note. Strategies: UWM, Unit weight model; WADD, Weighted additive model; MIN, Minimalist; TTB, Take The Best Distributions of cue validities; L-high, Linear cue distribution with high validities; L-low, Linear cue distribution with low validities; J-flat, Flat J-shaped cue distribution; J-steep, Steep J-shaped cue distribution.

MIN; differences were 9 and 5%). Moreover, in both environments with linearly distributed validities, the compensatory decision strategies (UWM and WADD) gained on average an increase of 12% points in accuracy by considering all cues when compared to the respective simple group heuristics (MIN and TTB).

If decisions were made in environments in which cue validities follow a J-shaped distribution, the comparison between the compensatory and noncompensatory decision strategies yielded a different picture. In these environments, TTB outperformed UWM by 16% points and even slightly exceeded the performance of WADD. In contrast to the linear distributions, the validity-based decision strategies (WADD and TTB) achieved a much higher accuracy than the strategies that ignored cue validities (UWM and MIN).

In sum, if cue validities were linearly distributed, the compensatory decision strategies outperformed the frugal noncompensatory heuristics by 12% points. Conversely, in environments with a J-shaped distribution of cue validities, TTB performed much better than UWM (difference of 16% points) and even slightly outperformed WADD (difference of 2% points).

5.2. *Does the quantity of shared information matter?*

While the results of Simulation 1 were conditioned on the fact that all members shared all of the information, Simulation 2 tested whether the effects of the distributions of cue validities would be replicated in environments where information was not completely shared: does group performance drop if group members have less information? To answer this question, the second simulation systematically varied the quantity of shared cue values within each of the four distributions of cue validities under the restriction that each piece of information was always known by at least one group member. Thus, the group as a whole had all of the cue values available as in the first simulation. In the most extreme case, in which each cue value was known by only one group member and in which, thus, no cue value was shared by group members, each of the four members received 15 (25%) of the 60 cue values. This number was systematically increased in 10 steps by adding five values per step (with each member knowing $20, 25, 30, \ldots, 60$ cue values). Thus, there were nine cases in which group members only had access to a partial set of information.

Table III shows the percentage of correct individual and group decisions (a) when each group member knew 15 cue values and no information was shared (25%); (b) when each group member had access to half of the information (30 cue values or 50%); in this condition, each cue value was, on average, shared by two group members; and (c) when not all group members shared all information, that is, across the nine cases in which group members only had access to a partial set of information ($15, 20, 25, 30, \ldots, 55$ out of 60 cue values, [*M* (25–92%)]).

As indicated in Table III, the mere quantity of shared information had only a minor effect on group performance. On average, the simulated groups achieved more accurate inferences if all cue values were shared as compared to conditions where no cue value was shared. This difference (on average, 6% points) was mainly due to the L-high condition, in which the largest difference between the conditions of 60 and 15 cue values appeared (on average, 10% points). Because the quantity of shared information did not have strong effects on group performance, the relationships between the decision strategies and the distribution of cue validities reported in Simulation 1 remained stable and were robust across different amounts of shared information.

The finding that the quantity of shared information does not strongly affect group performance seems to be counterintuitive (see Stasser, 1988, 1992). Table III offers one potential explanation for this finding: The majority rule compensated for impairments of performance at the individual level. As is indicated by the numbers in parentheses in Table III the effect of the quantity of shared information was much larger on the level of the individual group members than on the group level. On the individual level, the average difference between the conditions of 60 and 15 cue values was 12% points which is twice as high as the observed difference on the group level. How can this difference be explained? When the individuals had access to all of the information and used either UWM, WADD, or TTB, performance of the individual group members and the group was almost identical as is indicated by the 60 cue value condition in Table III. This is because in those cases where a strategy yielded an unequivocal decision, the four members arrived at the same decision. In other words, when each group member was fully informed, typically, all four members were correct or all four members were wrong. As a consequence, the majority rule performed as well as the individual group members on average. Conversely, if the individual group members used MIN or if they did not share all available information, then there was much more variation between their decisions. However, because the likelihood that an individual was correct was above chance, the majority rule improved group accuracy (see Reimer et al., 2005). Specifically, the majority rule enhanced group performance compared to the average individual group member in exactly those cases, in which a faction of two or three group members favored the correct decision.

Taken together, the quantity of shared information did not have strong effects on group performance in the environment used in the present simulation. Thus, the findings of Simulation 1 concerning the match between member decision strategies and the distribution of cue validities generalize across different amounts of shared information. Comparisons between individual and group accuracy indicate that the majority rule compensated for wrong decisions made by some group members.

5.3. *Does the quality of shared information matter?*

So far, the distribution of cue validities in the set of information given to group members has, on average, matched the distributions of cue validities in the environment. To see what will happen if this match is distorted, we ran another set of simulations in which information was distributed in a biased way such that values either on the most valid or on the least valid cues had a higher chance of being shared. This simulation was based on the idea that the quality of shared information might have a stronger effect on group performance than the mere quantity of shared information. The quality of shared information might vary because of differences in group members' expertise: group members may vary with respect to their knowledge about what the good cues are and knowledge about the cue values of those good cues.

Simulation 3a. Similar to the previous simulations, the available information was first randomly distributed among group members. However, in this simulation, each group member then filled up his or her set of known cue values to 50% by randomly drawing additional information—in one condition exclusively from the 10 most valid cues and in another condition exclusively from the 10 least valid cues. As a consequence, each group member had access to half of the available cue values as in the 50% condition of Simulation 2, but group members were more likely to share information either on the 10 most or on the 10 least valid cues. As can be seen in Table IV this variation did not exert strong effects on the performance of MIN and TTB. However, it strongly affected the performance of UWM in the two environments in which cue validities were moderately high on average (i.e., in the L-low and J-flat environments; see the framed numbers in Table IV). In addition, this variation also affected to some degree the performance of WADD in the L-low condition.

Simulation 3b. Because TTB looks up cues in an order established by their validity, this heuristic should be mainly affected by the degree to which the most valid cues are known by group members. To demonstrate this relationship, in one condition of Simulation 3b, three out of four group members received all cue values on the 10 most valid cues but no information on the 10 least valid cues. In another condition, three group members received all cue values on the 10 least valid cues but no information on the 10 most valid cues. In both conditions, all the remaining cue values were given to the fourth group member. Thus, in one condition of Simulation 3b, three group members did not know and could therefore not use the 10 least (most) valid cues at all. Such situations can, for example, arise if group members have

TABLE IV

Accuracy of group decisions (i.e., percent correct inferences) according to the quality of shared information (Simulation 3a)

Decision strategy	Cue validities	Distributions of cue validities			
		L-high	L-low	J-flat	J-steep
UWM	Most valid cues	85	69	60	44
	Least valid cues	84	48	46	43
WADD	Most valid cues	84	71	70	59
	Least valid cues	84	59	65	54
MIN	Most valid cues	67	47	46	40
	Least valid cues	64	42	39	36
TTB	Most valid cues	68	52	70	62
	Least valid cues	67	54	67	56

Note. Strategies: UWM, Unit weight model; WADD, Weighted additive model; MIN, Minimalist; TTB, Take The Best; Distributions of cue validities: L-high, Linear cue distribution with high validities; L-low, Linear cue distribution with low validities; J-flat, Flat J-shaped cue distribution; J-steep, Steep J-shaped cue distribution. The manipulation in Simulation 3a strongly a affected the performance of UWM in the L-low and J-flat environments as indicated by the framed numbers.

access to different information sources or systematically differ in expertise. Whereas UWM performed almost equally well in Simulations 3a and 3b, this is only partly true for the non-compensatory heuristics. If a majority of group members only had knowledge about the 10 least valid cues, performance of TTB dropped dramatically, demonstrating that the accuracy of TTB depends on the degree to which the most valid cues are shared (see the framed numbers in Table V).

Simulation 3c. The simulations described so far specify conditions, under which the individual group members' decision strategies affect group performance. However, there are also situations in which group performance is not strongly affected by the individual members' decision strategies. Consider, for

TABLE V

Accuracy of group decisions (i.e., percent correct inferences) according to the quality of shared information (Simulation 3b)

Decision strategy	Cue validities	Distributions of cue validities			
		L-high	L-low	J-flat	J-steep
UWM	Most valid cues	83	73	65	46
	Least valid cues	81	44	42	40
WADD	Most valid cues	82	71	73	58
	Least valid cues	82	44	37	41
MIN	Most valid cues	78	56	52	42
	Least valid cues	74	44	40	37
TTB	Most valid cues	78	56	73	61
	Least valid cues	70	42	31	39

Note. Strategies: UWM, Unit weight model; WADD, Weighted additive model, MIN, Minimalist; TTB, Take The Best. Distributions of cue validities: L-high, Linear cue distribution with high validities, L-low, Linear cue distribution with low validities; J-flat, Flat J-shaped cue distribution; J-steep, Steep J-shaped cue distribution. The manipulation in Simulation 3b strongly affected the performance of Strategies that consider cue validities (WADD and TTB) in the L-low and J-flat environments as indicated by the framed numbers.

example, a situation, in which most group members have access to only a few cues with very high or very low validities. Such a situation was used in Simulation 3c, where three group members shared all of the information on 3, instead of 10, of the most (or least) valid cues, and had no access to the remaining 17 least (most) valid cues. The forth group member had all of the information on the remaining 17 least (most) valid cues so that the group as a whole still had all of the information. A comparison of Tables V and VI reveals that this change had almost no effect on the performance of TTB. This is hardly surprising given that TTB did not consider, on average, more than the three most valid cues. In contrast,

TABLE VI

Accuracy of group decisions (i.e., percent correct inferences) according to the quality of shared information (Simulation 3c)

Decision strategy	Cue validities	Distributions of cue validities			
		L-high	L-low	J-flat	J-steep
UWM	Most valid cues	76	56	69	58
	Least valid cues	66	35	36	32
WADD	Most valid cues	75	55	72	62
	Least valid cues	61	37	37	34
MIN	Most valid cues	73	53	68	56
	Least valid cues	65	35	34	32
TTB	Most valid cues	73	53	71	61
	Least valid cues	62	33	35	31

Note. Strategies: UWM, Unit weight model; WADD, Weighted additive model, MIN, Minimalist; TTB, Take The Best. Distributions of cue validities: L-high, Linear cue distribution with high validities, L-low, Linear cue distribution with low validities; J-flat, Flat J-shaped cue distribution; J-steep, Steep J-shaped cue distribution.

the accuracy of MIN strongly improved in those environments in which cue validities followed a J-shaped distribution and a majority of group members had access to the most valid cues. In Simulation 3c, MIN gained much from *decreasing* the amount of shared information because three group members using MIN then had to draw a cue from among the 3 instead of 10 most valid cues. As a consequence, MIN performed almost as well as TTB. On the other hand, the losses were relatively weak if three members using MIN had to draw from among the three (instead of 10) least valid cues because the average validity of the three least cues did not differ much from that of the 10 least valid cues. As can be also seen in Table VI in this situation, in which three out of four group members only had knowledge about cues with very high or very low validities, all four decision strategies performed almost equally well.

6. DISCUSSION

In the present paper, we have applied the approach of simple heuristics (Gigerenzer et al., 1999) to group decision making. In a set of Monte-Carlo studies, four simulated group members had to select the best of three candidates. Performance was measured in terms of the percentage of choices in which the candidate with the highest criterion value was selected rather than the matches with a UWM, which is often used as a benchmark in group research (e.g., Stasser, 1992). The performance of UWM was compared with the performances of two fast and frugal heuristics and of a weighted additive model, WADD, which takes the cue validities into account. To explore the ecological rationality of the decision strategies, the distribution of cue validities was systematically varied. In addition, we varied how the available information was distributed among group members. Note that even though the simulations focused on the decision strategies that may be used by individual group members, the effects of the quantity and quality of shared information—which constitutes another important aspect of the environment in which groups have to make decisions—can only be understood from a group-level perspective.

The simulations clearly showed that the decision strategies used by the individual group members can exert strong effects on group performance. These effects were much stronger than the effects that were due to the mere quantity of shared information items that were known by the simulated group members at the outset of the group decision process. For example, in the J-flat condition, groups consisting of members using TTB outperformed groups with members using UWM even when the simulated group members in the former did not share a single cue value (66% correct) but group members in the latter shared all pieces of information (55% correct). Thus, in the environments used here, it was not the mere quantity of shared information that affected group performance, but rather how the information was processed. However, it is important to note that we simulated homogeneous groups in which members always used the same decision strategy. The effects of the amount of shared information may be larger in heterogeneous groups in which group members are less likely to arrive at the same individual decision when they share a large amount of cue values. In such a situation, the majority rule can not only compensate for a lack of individual knowledge but also improve accuracy when group members have full information.

Moreover, our simulations revealed that good group decisions do not always require exhaustive information processing. In environments in which validities were high and linearly distributed, UWM selected the candidate with the highest criterion value more often than the simple group heuristics and performed as well as WADD. In contrast, when cue validities followed a J-shaped distribution, the much more frugal TTB performed better than UWM and even slightly outperformed WADD. This pattern was fairly independent of the number of cue values that were shared among group members, even though performance was somewhat better if all pieces of information were shared than if all pieces of information were unshared. This observation, namely, that the quantity of shared information did not strongly affect accuracy, also supports the claim that less information does not necessarily yield poorer decisions. In contrast, the quality of shared information had stronger effects on group performance than the mere quantity. Specifically, systematic allocation of information in favor of cues with high or low validities revealed that the performance of UWM mainly depended on mean validity, whereas the performance of TTB was more strongly affected by the degree to which the most valid cues were shared. This difference decreased in a condition in which a majority of group members only had access to a few cues with very high or very low validities. Then, all four decision strategies performed almost equally well (cf. Table VI)

6.1. *The ecological rationality of simple group heuristics*

The repertoire of simple heuristics, available to a given species at a given point in its evolution, has been called its "adaptive toolbox" (Gigerenzer and Selten, 2001). An interesting issue concerns 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. Consistent with the notion of adaptation to the environment, strategy selection may be informed by the structure of information in the environment (Rieskamp and Otto, 2005, unpublished). In fact, the performance of the decision strategies in the present simulations depended on the environment in which they were tested: the distribution of cue validities and the quality of shared information determined whether or not the decision strategies achieved different accuracy scores and which strategy performed best.

We can thus add our results to the list of previous studies concerning the ecological rationality of simple heuristics. For instance, Hogarth and Karelaia (2003) classified environments according to the degree to which the weights of the cues are noncompensatory. They found that the superiority of Take The Best over UWM was most pronounced in environments that were strictly noncompensatory as defined by Martignon and Hoffrage (2002), that is, in environments in which the weight of any particular cue was higher than the sum of all weights of cues with lower weights. The more the distribution of cue weights deviated from such a set of noncompensatory cues, the less pronounced was the superiority of Take The Best over UWM, until at some point UWM started to yield better performance. This result is consistent with our observation that TTB performed better than UWM in environments in which cue validities followed a J-shaped distribution, while UWM was superior in those environments in which cue validities were linearly distributed. Note that on Hogarth and Karelaia's (2003) scale ranging from strictly noncompensatory to fully compensatory environments, our J-shaped environments would be located toward the noncompensatory end, whereas our environments with linear distributions of cue validities would be located toward the compensatory end.

Other environmental features—which we did not vary in the present simulations—are the number of alternatives, the number of cues, and the inter-correlations between cues. Martignon and Hoffrage (2000) have shown that for pair-wise comparisons in environments with scarce information, TTB has a higher chance of outperforming UWM than vice versa. In contrast, in environments with abundant information UWM achieves perfection, which is not the case for TTB (for technical definitions of scarce and abundant, see Martignon and Hoffrage, 2002). We suggest that future research on the performance of group heuristics should vary the number of candidates and the number of cues. Based on Martignon and Hoffrage's theorems about scarce and abundant information, our prediction would be that increasing the former and decreasing the latter will favor TTB and will be of disadvantage for UWM. We also did not vary the inter-correlations between cues and because cue values were generated randomly, the vast majority of environments had average inter-correlations close to zero (see Table II). systematic manipulation of the inter-correlation structure is another interesting issue that requires further investigation (for a step in this direction, see Hogarth and Karelaia, in press). Increasing the inter-correlations between cues makes information more redundant which may lead one to require fewer cues. Empirical evidence, however, suggests that people do not restrict their information acquisition accordingly—a phenomenon that Karelaia (2004) has termed the "lure of consistency."

In our simulations, we focused on the impact of the individual group members' decision strategies on group decisions and aimed to explore the ecological rationality of four group decision strategies that differ in how the information is processed by group members. Note that the comparisons of these four strategies were based upon a majority decision rule applied to the group members' individual decisions, and, consequently, that the conclusions drawn about the ecological rationality of the four strategies are conditioned on the application of this aggregation rule. Whether the results also hold if groups applied a different aggregation rule is another interesting question for future research. Likewise, it would be interesting to simulate heterogeneous groups in which members us different decision strategies (for a comparison of different aggregation rules, see Hastie and Kameda, 2005; Reimer and Katsikopoulos, 2004).

6.2. *The relevance of simple group heuristics for real groups*

Decision strategies can be classified along several dimensions: (a) the aggregation level, that is, whether they aggregate across individual decisions (social combination approach) or across cues (social communication approach); (b) the task they can solve (e.g., estimation tasks or choice tasks); (c) their decision costs and their frugality (e.g., exhaustive versus limited information-processing); and (d) their performance with respect to an outside criterion or a benchmark. In the case of group decision making, additional dimensions exist (e.g., Vroom, 1969; also see Adamowicz et al., in press). According to Vroom (1969), group decisions can be classified according to (a) their accuracy, (b) the acceptance or commitment of the members to the decision, and (c) the time needed to come to a decision. With regard to accuracy and frugality, our simulations have shown that the TTB heuristic deserves further attention from a prescriptive point of view. With respect to acceptance or commitment, however, whether real groups would embrace the present approach of fast and frugal heuristics is questionable—after all, the decision might have been assigned to a group because it was presumed that a better decision would be made if more people contribute to the process and if more information is exchanged. Such a belief is likely to counteract the use of simple group heuristics.

On the other hand, research on group decision making has revealed that groups usually do not exchange all of the available information anyways. Typically, group members mainly discuss what is already known to all members at the outset of a group decision process, whereas unique, unshared information is less likely to be mentioned during discussions (see Wittenbaum and Stasser, 1996, for an overview). As a consequence, recent research has focused on variables that moderate this sampling advantage of shared information and on interventions that may instigate the exchange of unshared information. These interventions are based on the assumption that higher quantities of shared information are more conducive to better decision making. Interestingly, most of these interventions demonstrate only marginal effects (Larson et al., 1994; Mennecke, 1997; Stasser et al., 1989, 1995; Stewart et al., 1998; for effective interventions, see Hollingshead, 1996; Schittekatte and van Hiel, 1996). We suggest that it is first important to consider the nature of the environment, and whether aspects of the environment are amenable to improvements of group performance driven by the sharing of information.

As mentioned previously, the integration of the fast and frugal approach with group decision making introduces several empirical questions that have yet to be addressed. Do and can groups use fast and frugal heuristics when forming a decision, and to what extent (for an example, see Reimer and Katsikopoulos, 2004)? In which types of situations are groups able to exploit the structure of the environment by adapting their decision strategies (see Reimer et al., 2005)? While more empirical data are needed to answer these questions, we believe the results from the current simulations suggest that fast and frugal heuristics may be both attractive and adaptive for decision-making groups.

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NOTES

1. There are various ways to define the weight of a cue. Following Martigrion and Hoffrage (2002), we implemented WADD using g rather than v as weights because of the following reason: For a cue which predicts the correct choice only at chance level, g equals zero, which is the weight one would intuitively assign to a nonpredictive cue, whereas v equal 0.5. TTB is not affected by the definition which is used because v and g establish the same order of cues.
2. We initially specified the four distributions of cue validities (as graphed in Figure 1) and defined the rank order of the 20 fictitious candidates (as shown in Table I). We then produced 200 cues with a maximum discrimination rate and a validity of 1 by assigning the 10 best-suited candidates a '+1' and the 10 least-suited candidates a '−1' on every cue. Next, we added an error term to each of these cue values. Then, new cue values were computed on the basis of a median split. This procedure yielded cues with a maximum discrimination rate but with different cue validities. From the set of 200 cues, we selected the 20 cues that fit the respective distribution. This procedure was repeated in each of the four distributions for which we chose different error terms (e.g., the error term was smaller in the L-high than in the L-low environment).

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