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ADAPTIVE MECHANISMS FOR TREATING MISSING INFORMATION: A SIMULATION STUDY

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People often make inferences with incomplete information. Previous research has led to a mixed picture of how people treat missing information. To explain these results, the authors follow the Brunswikian perspective on human inference and hypothesize that the mechanism's accuracy for treating missing information depends on how it is distributed in a certain environment. The hypothesis is supported by the results of a simulation study, which also shows that the mechanism for treating missing information has a much stronger impact on overall accuracy than the most accurate inference strategies considered. The conclusion is that how people react to missing information could be an adaptive response to specific environments.

When making inferences, people are often confronted with incomplete information. Looking for a healthy meal at a restaurant, for instance, we often do not have much detail about the entrées on the menu (e.g., the amount of cholesterol, fat, or preservatives in the dishes, or the cooking methods used) to help us infer which dish would be the wisest choice. Nevertheless, even with incomplete information, people infer which is the healthier option and make their choices. In the present article, the question addressed is how people should make inferences despite incomplete information.

The question of how people deal with incomplete information has attracted increasing interest (see Ganzach & Krantz, 1990; Huber & McCann, 1982; Jaccard & Wood, 1988; Johnson & Levin, 1985; Kardes, Posavac, Cronley, & Herr; 2008;

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White & Koehler, 2004; Zhang & Markman, 1998, 2001). The research, however, has led to a rather mixed picture. Several authors, for instance, have argued that when people confront an inference situation with incomplete information, missing information is treated as the average of the observed information (Ganzach & Krantz, 1990; Slovic & MacPhillamy, 1974; White & Koehler, 2004) or the most frequently observed information (i.e., the mode, Jaccard & Wood, 1988).

Alternatively, others have argued that individuals sometimes treat missing information as if it were negative (Huber & McCann, 1982; Jaccard & Wood, 1988; Johnson, 1987, 1989; Johnson & Levin, 1985; Lim & Kim, 1992; Lim, Olshavsky, & Kim, 1988; Meyer, 1981; Yamagishi & Hill, 1981, 1983; Yates, Jagacinski, & Faber, 1978). Presumably, the assumption is that missing information has been withheld because it would lead to a negative evaluation. For instance, when a personnel manager tries to find a new employee for an open position in a company, the applications often are not complete. Possibly, those candidates who are less competent might have incomplete applications more frequently.

In contrast, sometimes individuals process unknown information as if it were positive, especially when positive information is more prevalent in the inference situation (see, e.g., the studies of Levin, Johnson, & Faraone, 1984; Levin, Johnson, Ruso, & Deldin, 1985; Levin, Mosell, Lamka, Savage, & Gray, 1977). For instance, casino managers initially assume that their guests can cover their bets unless a negative report has been made in the past. Likewise, road users expect good weather conditions as long as no warning is given on the radio; that is, when explicit information about the weather conditions is missing, people regard the missing information as a positive signal. In these cases, missing information is positively correlated with the criterion value that must be predicted. Finally, people sometimes just use whatever information is available and simply ignore missing information (see Kardes et al., 2008; Sanbonmatsu, Kardes, & Herr, 1992; Simmons & Lynch, 1991). In summary, the empirical evidence shows a large heterogeneity in how people treat missing information, leading to the question of how this heterogeneity can be explained.

Mechanisms for Treating Missing Information as Adaptations to the Environment

The present study was undertaken to solve the question of why people respond in different ways to incomplete information, by following a Brunswikian perspective on human inference (e.g., Brunswik, 1943, 1956, 1957; Gigerenzer, Hoffrage, & Kleinbölting, 1991; Hammond, 1996). The interrelation between the organism and its environment is the basic premise of Brunswik's theory (Brunswik, 1957). This general premise took shape in the well-known lens model (Brunswik, 1956), which analyzes the structure of the environment and addresses the organism's adjustment to that environment (see also Hammond, 1996; Hammond & Stewart, 2001; Vicente, 2003). When this perspective is applied to an inference situation with incomplete information, a reasonable assumption is that people's judgment processes largely reflect the underlying structure of an environment. They will then most likely apply the mechanism for treating missing information that leads to the highest inferential accuracy in a certain environment. For instance, people would treat missing information as negative if they suspect it was actively withheld for that reason. This is a strong argument, but related research has shown that people's reasoning can often be understood as an adaptation to specific environmental situations (Anderson, 1991; Brunswik, 1943; Garcia-Retamero, 2007; Garcia-Retamero & Hoffrage, 2006; Payne, Bettman, & Johnson, 1988, 1993; Rieskamp, 2006a, 2006b; Rieskamp, Busemeyer, & Laine, 2003; Rieskamp & Otto, 2006).

Which Characteristics of the Environment Influence the Accuracy of the Mechanisms for Treating Missing Information?

The mechanisms for treating missing information are the building blocks of a complete inference strategy. Therefore, the study of the accuracy of these mechanisms depends on the inference strategy that is employed and on how that strategy performs in a certain environment. For example, let's return to the restaurant situation: which of two dishes on the menu is healthier? To make this inference, we could use the information of several cues, such as the amount of cream or butter in the dishes, the cooking method (i.e., whether the entrée is broiled or fried), the number of nutrients, or the food source (i.e., animal or plant origin; see Figure 1). The cues could have either a positive or a negative value for each dish, with positive values indicating a high criterion value (i.e., a healthy dish) and negative values indicating a low criterion value (i.e., an unhealthy dish). Each cue has a certain validity, defined as the conditional probability of making a correct inference when the cue discriminates—that is, has a positive value for one dish and a negative value for the other.

	Dish A	Dish B
Amount of Cream .90	+	+
Cooking Method .80	+	–
Nutrients .70	–	+
Food Source .60	–	+

Figure 1. Illustration of a two-alternative forced-choice task for which take-the-best (TTB) and weighted additive (WADD) can be applied. Which of the two alternatives described on several dichotomous cues has a higher value on a quantitative criterion has to be inferred.

Several inference strategies could be applied for this task. To decide which dish would be healthier, people could, for instance, select a simple lexicographic strategy called take-the-best (TTB; see Gigerenzer & Goldstein, 1996, 1999). This strategy searches for cues in the order of their validity and stops searching when the first discriminating cue is found. The first discriminating cue found is used to make the inference. In our example, TTB would start searching whether the amount of cream in the dishes is high or low. If this cue does not discriminate between the dishes, the second most valid cue would be considered (i.e., the cooking method), and the dish with the positive cue value would be selected (i.e., dish A).

Alternatively, a compensatory weighted additive (WADD) strategy could be used. For each dish, WADD computes the sum of all cue values multiplied by their cue validities and selects the dish with the largest sum (i.e., dish B in our example). WADD can also be implemented by determining a weighted difference. That is, the cue with the highest validity is considered first. The difference between the cue values is computed and multiplied by the cue's validity. This method of implementing WADD has several advantages: Whenever a cue does not discriminate between two alternatives, the difference is zero. Consequently, no additional computations have to be performed on this cue. Moreover, it allows WADD to limit the information search. For instance, imagine that the three most valid of six cues favor one alternative. In this case, the remaining three cues do not need to be looked up because they cannot change WADD's preliminary decision. Therefore, a limited search for WADD is, in principle, also possible (for this implementation of WADD, see also Tversky, 1969).

Previous research has shown that TTB and WADD are able to predict people's inferences fairly well, with the predictive advantage for one or the other strategy depending on the inference situation (see Bröder & Schiffer, 2003; Garcia-Retamero, Hoffrage, & Dieckmann, 2007; Garcia-Retamero, Hoffrage, Dieckmann, & Ramos, 2007; Hoffrage, Garcia-Retamero, & Czienskowski, 2008; Newell & Shanks, 2003; Rieskamp, 2006a; Rieskamp & Hoffrage, 2008; Rieskamp & Otto, 2006). Naturally, TTB and WADD represent only two possible inference strategies (for overviews, see Garcia-Retamero & Dieckmann, 2006, or Rieskamp & Hoffrage, 1999, 2008). WADD represents a prototypical compensatory strategy that integrates all available information, and TTB represents a prototypical noncompensatory strategy that does not integrate information. Our conclusions, however, can be extended to alternative inference strategies, which are not reported here for the sake of simplicity and brevity. The focus on WADD and TTB is useful because both strategies have been shown to be accurate in predicting people's inferences under various conditions, as the above-mentioned studies have shown. However, none of these previous studies has explored the question of how the different mechanisms for treating missing information influence the accuracy of these strategies.

A critical characteristic of the environment that could influence the accuracy of the mechanisms for treating missing information is the way missing information is distributed in the environment. Many authors assume (e.g., White & Koehler, 2004) that the likelihood of encountering missing information is the same across alternatives (i.e., missing information is *uniformly distributed*). For instance, when predicting which of two dishes on a menu would be healthier, one might assume that missing cue values will occur with the same probability for both dishes (e.g., the likelihood of finding missing information about the amount of fat in the dishes or the cooking methods used would be equal for both alternatives).

However, in many inference situations, the assumption of uniformly distributed missing information is not justified. In contrast, sometimes missing information is more likely to occur for alternatives that have a low criterion value. Further, the dishes that are less healthy frequently have incomplete information about the amount of cream and butter they contain, or the cooking methods used. In such an environment, missing information is *conditionally distributed* depending on the criterion value. Depending on the environment, different mechanisms for treating missing information would be optimal for making inferences. If the performance of inference strategies and their mechanisms for treating missing information depend on the environment, this could explain why people deal with incomplete information differently when aiming for high inference accuracy; and it would also explain the mixed results in the literature of how people treat missing information.

A computer simulation was therefore performed to explore the impact of the distribution of missing information on the accuracy of inference strategies. One goal of the simulation was to examine whether when aiming for high inference accuracy, it is more important to select the optimal inference strategy or the optimal mechanism for treating missing information.

Simulation Study

Previous researchers have examined the accuracy of various inference strategies in solving everyday inference problems. For instance, Gigerenzer and Goldstein (1996) tested the performance of TTB against alternative strategies, such as multiple regression (see also Gigerenzer, Todd, & the ABC Research Group, 1999). They found that the strategies closely matched in performance. Moreover, when predictions were made for independent data in cross-validation,[1] TTB even outperformed multiple regression across a wide range of inference problems (Czerlinski, Gigerenzer, & Goldstein, 1999). Hogarth and Karelaia (2005) generalized this result to an inference situation with continuous as opposed to dichotomous cues (see also Hogarth & Karelaia, 2006, 2007). Furthermore, Juslin and Persson (2002) and Chater, Oaksford, Nakisa, and Redington (2003) showed that TTB behaves comparably to connectionist, exemplar-based, and decision-tree algorithms. However, the influence of missing information on the performance of inference strategies received little attention in the above-mentioned literature. For instance, Gigerenzer et al. (1991) assumed that when confronted with missing information, people will simply ignore this information. That is, when comparing two alternatives, they will ignore cues that offer only partial information (i.e., have missing information for one alternative), so that only cues with complete information determine the inference. In contrast, Gigerenzer and Goldstein (1996) proposed that if a cue provides positive information for one of the alternatives and has missing information for the second, the interpretation should be that this cue provides positive support for the first alternative. Thus, different assumptions about how missing information is treated have been made.

However, none of the aforementioned authors systematically explored how these and other well-known mechanisms for treating missing information affect the accuracy of inference strategies. This systematic analysis was the goal of the present simulation. Specifically, the following mechanisms were tested: ignoring missing information, treating missing information as if it were negative, treating it as if it were positive, treating it as if it were the average, and treating it as if it were the mode of the available information. Moreover, no one has studied how the mechanisms react to different environment characteristics. In the present simulation, the first goal was to test how sensitive the mechanisms are to increasing amounts of missing information. The second goal was to test how these mechanisms affect the accuracy of two inference strategies, namely, TTB and WADD, in environments where missing information is distributed differently.

1 Cross-validation refers to the analysis of the accuracy of a decision strategy when, after fitting it to one part of a data set (training set), it is applied to the other part (test set).

In one environment, missing information was uniformly distributed, so that it did not correlate with the criterion value. In the second environment, missing information was conditionally distributed, so that it correlated negatively with the criterion value.

The use of data for a large variety of inference problems that have been studied in different disciplines avoided the limitations that would result from a focus on a particular inference problem. The disciplines included were psychology, economics, and computer science. The inference task for the different problems was to always infer, based on several cues, which of two objects had a higher criterion value. Altogether, 10 different inference problems were considered, including the expenses of U.S. airlines, the dropout rate at Chicago high schools, and the lifespan of certain mammals. Table 1 provides a detailed description of the 10 environments. They differed by the number of objects considered (ranging from 24 to 181 objects) and the number of cues provided for making an inference (ranging from 3 to 12 cues).

In general, the expectation was that the accuracy of the inferential strategies would decrease when the amount of missing information increased. However, the decrement in accuracy would depend on the implemented mechanism for treating missing information and on how the mechanism fits with the environmental characteristic—that is, the way missing information is distributed in the environment. The assumption was that the treatment of missing information as if it were negative would do well when missing information was conditionally distributed depending on the criterion value. In contrast, when missing information was uniformly distributed, the treatment of missing information as the average should lead to the highest accuracy. Thus, no single mechanism is best for treating missing information; instead, the mechanism's accuracy should depend on the environment.

As suggested by Gigerenzer et al. (1991), ignoring missing information could also lead to high accuracy because wrong inferences about the missing cue values are avoided, and the final inference relies on only information that is known. However, when cues have a high validity, it might be more adaptive to rely on them even if they offer only partial information. The underlying logic of treating missing information positively is similar to that of treating missing information as if it were negative: It just makes the opposite assumption. This mechanism should be adaptive when unknown information is positively correlated with the criterion value. Finally, the last mechanism considered was treating missing information as the most frequently observed information (i.e., the mode). This mechanism has a similar underlying logic to treating missing information as the average because an expectation is formed about the missing information on the basis of the available information. However, despite this similarity, the consequences of its use can be very different. This mechanism might work well in environments where the cues have very skewed distributions—that is, environments in which positive (negative) cue values are very frequent so that a better assumption might be that missing information is most likely positive (negative). Whether this mechanism can also perform well when the distribution of positive and negative cue values is not skewed is an open question.

Another open question is to what extent the different mechanisms for treating missing information influence the accuracy of the inference

Table 1
Description of the 10 Everyday Inference Problems Used in the Simulations

Description of the Real-World Problems	Average Validity	Validity Range
Dropout rate at high schools. Predicting the dropout rate at 63 Chicago high schools (Rodkin, 1995), described by the following 12 most valid cues: attendance rate, graduation rate, percentage of low income students, average class size, percentage of white students, percentage of Asian students, average composite ACT score, reading score, math score, science score, social science score, and writing score	0.71	0.76 - 0.62
Amount of rainfall after cloud seeding. Predicting the amount of rainfall after cloud seeding for 24 weather observations (Woodley, Simpson, Biondini, & Berkeley, 1977), described by the following 6 cues: action, days after experiment, suitability for seeding, percent cloud cover on day of experiment, prewetness, and echo motion	0.62	0.76 - 0.51
Number of species at Galapagos islands. Predicting the number of species for 29 Galapagos islands (Johnson & Raven, 1973), described by the following 6 cues: endemics, area, elevation, distance to next island, distance to coast, and area of adjacent island	0.73	0.97 - 0.52
Homelessness. Predicting the rate of homelessness of 50 U.S. cities (Tucker, 1987), described by the following 6 cues: percentage of population in poverty, unemployment rate, public housing, mean temperature, vacancy rates, and population	0.58	0.68 - 0.52
Lifespan of mammals. Predicting the lifespan of 58 mammals (Allison & Cicchetti, 1976), described by the following 9 cues: body weight, brain weight, slow-wave sleep, paradoxical sleep, total sleep, gestation time, predation index, sleep exposure index, and overall danger index	0.74	0.93 - 0.54
Total expenses of firms. Predicting the total expenses of 158 firms (Christensen & Green, 1976), described by the following 7 cues: total output, wage rate, cost share for labor, capital price index, cost share for capital, fuel price, and cost share for fuel	0.61	0.98 - 0.51
Expenses of U.S. airlines. Predicting the costs of U.S. airlines using 90 observations (Greene, 2003), described by the following 3 cues: revenue passenger miles, fuel price, and load factor	0.95	1.00 - 0.85
Output of transportation firms. Predicting the output of transportation firms in 25 U.S. states (Zellner & Revankar, 1970), described by the following 3 cues: capital input, labor input, and number of firms	0.94	1.00 - 0.84
Expenses of electricity producers. Predicting the total expenses of 181 electricity producers (Nerlove, 1963), described by the following 7 cues: total output, wage rate, cost share for labor, capital price index, cost share for capital, fuel price, and cost share for fuel	0.64	0.99 - 0.51
Population of African countries. Predicting the number of inhabitant of 54 African countries, described by the following 7 cues: part of the Sahel zone, area size, OPEC membership, media citations in 2004, per capita income, inhabitants of capital, and illiteracy rate. Data was assembled on the basis of our own research, partly based on The World Factbook (Central Intelligence Agency, 2005)	0.70	0.84 - 0.50

strategies, TTB and WADD. It is not clear whether the influence of increasing amounts of missing information has the same detrimental effect on the accuracy of both inference strategies. A plausible assumption is that the effect of missing information will be less severe for WADD than for TTB. Since in WADD almost all of the available information is used to make an inference, the information that is present might be used to compensate for some information that is not available. In contrast, with the lexicographic strategy TTB, an inference is made based on only one single cue. If a cue does not provide information, other less valid cues might be considered, thereby reducing the accuracy of the strategy.

Furthermore, it is interesting to examine whether to reach the highest accuracy it is crucial to select the most accurate strategy (i.e., TTB or WADD) regardless of the mechanism for treating missing information; or whether it is more important to select the most accurate mechanism for treating missing information regardless of the inference strategy; or, finally, whether only by selecting the most accurate strategy and the most accurate mechanism for treating missing information can a substantial increase in accuracy be reached. For this purpose, the accuracy difference between TTB and WADD is related to the accuracy differences of the mechanisms for treating missing information. Perhaps the accuracy difference between TTB and WADD is so large relative to the accuracy differences of the mechanisms for treating missing information that selection of the most accurate inference strategy is crucial, regardless of how missing information is treated. In contrast, perhaps it is essential to select the best mechanism for treating missing information, because this could have a much stronger effect on accuracy than the selection of the right inference strategy.

In addition to strategy accuracy, a second evaluation criterion in this study was to examine the amount of information the strategies require when the different mechanisms are used for treating missing information (i.e., the frugality of the strategy). Because TTB stops the information search when the first discriminating cue is found, treating missing information as the average should lead to the highest frugality when implemented in TTB. Specifically, a cue with missing information on one alternative would discriminate between the two alternatives (and, consequently, the information search would be stopped) regardless of whether the second alternative has a positive or a negative value on this cue. In contrast, if missing information is processed as negative (positive), a cue with missing information on one alternative would discriminate between the alternatives only if the second alternative has a positive (negative) value on this cue. Finally, if missing information is ignored, the search would be stopped only if one alternative has a positive cue value and the second a negative. Therefore, this should be the least frugal mechanism when implemented in TTB. Furthermore, in WADD most of the available information is searched and then integrated into a weighted sum. Therefore, this strategy is expected to be less frugal than TTB regardless of which mechanism is selected for treating missing information.

Method

Decision situations with varying degrees of missing information were simulated. For each of the 10 problems, six levels of missing information were simulated, namely, 0, 25%, 50%, 75%, 90%, and 100% missing cue values. For instance, at the 25% level, 25% of the cue values were selected to be regarded as missing information. In one condition, the missing cue values were uniformly distributed, whereas in the second condition, the missing cue values were conditionally distributed depending on the criterion value. For the condition with uniformly distributed missing information, the cue values that were regarded as missing were selected with equal probability. For the second condition, the probability of each cue value being selected was determined by the use of an exponential function: $f(z_n) = (1/b)\exp(-z_n/b)$, with z as the z-transformed criterion value of each object and b as a scale parameter with a value of 4 for the simulations. In this condition, the smaller the criterion value the larger the probability of being selected to be regarded as missing. For each of the 10 inference problems, six levels of missing information and two distributions of missing information were examined, providing altogether 12 conditions. For each of these conditions, 1,000 instances of missing information were simulated. For each instance, different cue values were selected to be regarded as missing with the constraints mentioned above. The task consisted of inferring, for all possible pair comparisons of objects, which object has a higher criterion value on the basis of the available cues. For instance, when making an inference about the population size of African countries, all possible pairs of countries were determined. For all pairs, the inference was which country had the larger population. Examples of the cues were whether the country belongs to OPEC or whether the media coverage of the country is above or below the median. In general, for all environments, a median split was used to dichotomize cues with continuous values.

For each of the 1,000 instances of the 12 environment conditions, the accuracy of TTB and WADD was examined when the five different mechanisms were used for treating missing information. In addition, the levels of frugality were examined for each strategy—that is, the proportion of cues the strategy required to make decisions. As described earlier, TTB stops searching for information as soon as a cue discriminates. For WADD, limited information search is, in principle, also possible (see Rieskamp & Otto, 2006). If, for example, the two most valid of three cues favor one alternative, then the third cue cannot change a preliminary decision of WADD. So, the search can be limited by the assumption that WADD stops the search when additional cues cannot change a preliminary decision based on the required cues. This limited information search for WADD might not appear very plausible from a psychological point of view, because it requires that a person using such a strategy always determines a preliminary inference and compares this inference with the hypothetical inference of WADD with all cues used. Nevertheless, this limited information search process can be assumed for WADD because it restricts the amount of information that it requires and thereby leads to a more demanding competition between TTB and WADD about their frugality. For both strategies (i.e., TTB and WADD), the assumption is that they search cues in the order of cue validity.

In summary, the design of the simulation in this study varied (1) the distribution of missing information and (2) the amount of missing information. For dependent variables, two attributes were examined: (1) the accuracy, defined as the percentage of correct inferences for all pair comparisons, and (2) the frugality, defined as the average proportion of cues acquired to make an inference.

Results

The first report is how accurately the strategies solved the inference problems in the different environmental conditions. The second is how much information the strategies required for making an inference.

Accuracies of Strategies

Figure 2 shows the average inferential accuracy of the five mechanisms for treating missing information when implemented in TTB (Figure 2A) and WADD (Figure 2B) across the 1,000 simulated instances and the 10 inference problems. The figure shows the percentage of correct decisions for the different levels of missing information when missing information was both uniformly distributed and conditionally distributed depending on the criterion value (see also Table 2).

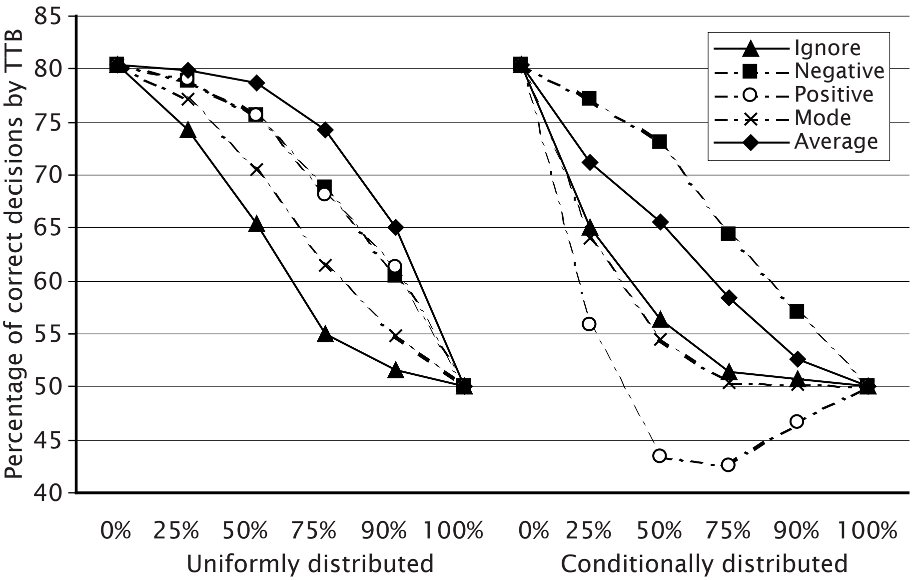


Figure 2. Percentage of correct decisions of the five mechanisms for treating missing information when implemented in TTB (A) and WADD (B) across different levels of missing information (0 to 100%) when unknown cue values were uniformly distributed (left side) or conditionally distributed on the criterion value (right side).

As predicted, with 71% correct inferences, treating missing information as the average achieved the highest accuracy in the environment with uniformly distributed missing information. In a similar vein, with 65% correct inferences, treating missing information as if it were negative outperformed the rest of the mechanisms in the environment with conditionally distributed missing information. So, which mechanism leads to the highest inferential accuracy depends on how missing information is distributed in the environment. These results illustrate that Gigerenzer and Goldstein's (1996) assumption of treating missing information as negative is the most adaptive mechanism in environments where missing information is negatively correlated with the criterion value.

Table 2
Average Percentage of Correct Decisions of the Five Mechanisms and Their Standard Deviation for Treating Missing Information When Implemented in TTB and WADD Across Different Levels of Missing Information When Unknown Cue Values Were Uniformly or Conditionally Distributed on the Criterion Value

Distribution	Missing Information (%)	Mechanism	Accuracy of TTB	SD of TTB	Accuracy of WADD	SD of WADD
Uniformly distributed	0	Ignore	80.37	8.06	77.76	7.89
		Negative	80.37	8.06	77.76	7.89
		Positive	80.37	8.06	77.76	7.89
		Mode	80.37	8.06	77.76	7.89
		Average	80.37	8.06	77.76	7.89
	25	Ignore	74.33	7.27	73.18	7.20
		Negative	78.83	8.19	76.67	8.26
		Positive	79.01	8.36	77.23	8.33
		Mode	77.09	7.24	75.16	7.17
		Average	79.83	8.85	78.19	8.80
	50	Ignore	65.45	5.20	63.93	5.16
		Negative	75.71	8.13	73.74	8.06
		Positive	75.69	8.49	73.43	8.46
		Mode	70.52	5.63	69.05	5.34
		Average	78.68	9.17	77.29	9.13
	75	Ignore	54.97	1.92	54.13	1.95
		Negative	68.79	6.53	67.36	6.31
		Positive	68.17	6.76	67.21	6.60
		Mode	61.46	4.05	60.59	3.83
		Average	74.33	7.89	72.45	7.83
	90	Ignore	51.56	0.42	50.58	0.49
		Negative	60.50	3.51	59.68	3.43
		Positive	61.24	3.41	60.22	3.35
		Mode	54.85	2.60	53.31	2.53
		Average	65.02	4.57	64.00	4.53
	100	Ignore	50.00	0.01	50.01	0.01
		Negative	49.98	0.00	50.01	0.01
		Positive	50.01	0.02	50.01	0.01
		Mode	50.01	0.02	49.98	0.02
		Average	50.00	0.01	50.00	0.02

Table continues on next page

Table 2 continued
Average Percentage of Correct Decisions of the Five Mechanisms and Their Standard Deviation for Treating Missing Information When Implemented in TTB and WADD Across Different Levels of Missing Information When Unknown Cue Values Were Uniformly or Conditionally Distributed on the Criterion Value

Distribution	Missing Information (%)	Mechanism	Accuracy of TTB	SD of TTB	Accuracy of WADD	SD of WADD
Conditionally distributed	0	Ignore	80.37	8.06	77.76	7.89
		Negative	80.37	8.06	77.76	7.89
		Positive	80.37	8.06	77.76	7.89
		Mode	80.37	8.06	77.76	7.89
		Average	80.37	8.06	77.76	7.89
	25	Ignore	64.99	3.07	63.73	3.26
		Negative	77.09	5.27	74.21	5.03
		Positive	55.89	4.12	55.29	6.02
		Mode	64.09	4.01	62.51	4.60
		Average	71.16	4.49	67.71	4.65
	50	Ignore	56.28	1.29	54.97	1.46
		Negative	73.08	4.10	68.96	5.17
		Positive	43.47	4.81	44.30	6.63
		Mode	54.46	4.87	53.37	5.39
		Average	65.62	4.75	62.64	4.74
	75	Ignore	51.45	0.35	51.03	0.40
		Negative	64.31	3.18	60.37	4.89
		Positive	42.60	4.30	43.80	5.43
		Mode	50.42	3.61	48.92	3.95
		Average	58.48	3.81	55.00	3.58
	90	Ignore	50.81	0.09	49.18	0.09
		Negative	57.04	1.52	52.24	3.00
		Positive	46.61	2.33	46.54	2.79
		Mode	50.28	1.26	49.52	1.39
		Average	52.59	2.33	49.70	1.78
	100	Ignore	49.98	0.00	50.00	0.01
		Negative	49.99	0.00	50.01	0.00
		Positive	50.02	0.01	50.01	0.01
		Mode	50.01	0.01	49.99	0.02
		Average	50.01	0.00	50.01	0.00

In general, the other mechanisms for treating missing information did not perform well. Surprisingly, with 62% correct inferences, ignoring missing information led to the lowest accuracy in the uniformly distributed environment. It also achieved poor accuracy in the conditionally distributed environment (i.e., 58%). This result illustrates that on average, forming expectations about missing information and using partial available information is better than simply relying on information that is known while ignoring what is missing. This result also emphasizes the necessity of testing whether people profit from incomplete information when making inferences.

Processing missing information as if it were positive or as the mode also led to low inferential accuracy. That treating missing information as positive in the conditionally distributed environment achieved a very low accuracy is not surprising. More surprising, though, is that treating missing information as the mode also produced poor performance. The reason is that for the inference problems considered, positive cue values were predominant, so that missing information was often treated as positive. This mechanism does not lead to high accuracy, especially when missing information is conditionally distributed.

As expected, when the amount of missing information increased, the accuracies of the mechanisms decreased, but not equally for all the mechanisms. When missing information increased from 0 to 90%, the accuracy of ignoring missing information, treating missing information as the mode, or treating it as positive dropped by 29%, 27%, and 25%, respectively, whereas treating missing information as negative or as the average decreased accuracy by only 21%. Thus, the former mechanisms not only produced poor performance on average, but they also reacted more sensitively to increasing amounts of missing information.

In the present study, the problems in the simulations differed by the number of objects considered and the number of cues provided for making an inference. These features, however, do not have a substantial influence on the results. In contrast, whether cues have a very skewed distribution (i.e., whether positive or negative cue values are frequent for an inference problem) has an impact on our findings. Specifically, in the few problems in which negative cue values were frequent (e.g., when predicting the total cost of the electricity producers, or the population size of African countries), increasing the amounts of missing information did not substantially affect the accuracy of treating missing information as negative, especially when this missing information was conditionally distributed. In contrast, for inference problems in which positive cue values were frequent, as is the case of predicting the dropout rates at Chicago high schools, the decrease in the accuracy of treating missing information as negative was severe in the conditionally distributed environment.

Surprisingly, the different mechanisms for treating missing information had a similar impact on the two inference strategies, which use information in very different ways. That is, the average accuracies for TTB and WADD were very similar, with 64% and 62% correct inferences across all implemented mechanisms, respectively. In general, the accuracy levels of the strategies were similar to each other regardless of which mechanism was implemented. Moreover, the accuracies of the strategies with different mechanisms for treating missing information were not affected differently by how missing information was distributed in the environments. This result is unexpected because in TTB an inference is made on the basis of only one single cue, and the different mechanisms for treating missing information have an impact on which cue is finally used to make the inference. In contrast, for each alternative, WADD integrates almost all of the available information into a weighted sum. Because of this difference, a difference is expected in the accuracy of the strategies depending on the implemented mechanism for treating missing information, which, however, were not observed.

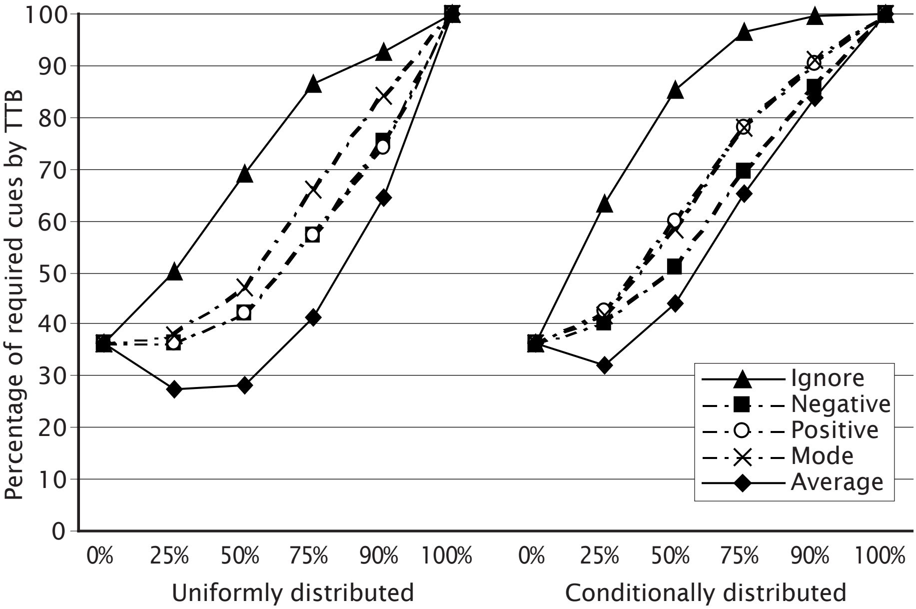
One important result of the simulations is the relative accuracies of the two inference strategies compared with the relative accuracies of the mechanisms for treating missing information. The two strategies, WADD and TTB, had very similar accuracy levels across all considered problems. In contrast, the accuracies of the strategies differed substantially with different mechanisms implemented for treating missing information. An important conclusion stems from this: In an environment with incomplete information, selecting the best inference strategy is less important than selecting the best mechanism for treating missing information.

Levels of Frugality of the Strategies

How do the different mechanisms for treating missing information affect the frugality of the strategies—that is, the amount of information required to make an inference? Figure 3 shows the percentage of cues required for TTB (Figure 3A) and for WADD (Figure 3B) to make an inference, differentiated for the five mechanisms for treating missing information and averaged across the 10 problems and the 1,000 instances. The figure shows the percentage of cues required when missing information was both uniformly distributed and conditionally distributed depending on the criterion value.

On average, with the use of 57% of the available information, TTB was much more frugal than WADD, which used 80%. Furthermore, the average number of cues the strategies used increased as the amount of missing information also increased. However, this increment differed substantially for TTB and WADD, depending on the implemented mechanism for treating missing information. When TTB is selected, treating missing information as the average achieved the highest frugality, with on average only 46% of cues used; and 74% of the cues were required when the amount of missing information increased to 90%. Treating missing information as the average led to a higher frugality of TTB when 25% or 50% of the cue values were unknown compared with complete knowledge. The explanation is that when one alternative has missing information for a cue and the other alternative has either a positive or negative cue value, treating the missing cue value as the average leads to a discrimination between the two alternatives, so that TTB stops its information search and makes an inference. However, when the amount of missing information increases above 50%, both alternatives often encounter missing information, so that the cue will not discriminate and TTB will search for further cues.

In contrast, ignoring missing information leads to an increase in information search. When TTB ignored cues with missing information, on average the strategy searched for 72% of the available information and even required 96% of the cues when the amount of missing information increased to 90%. The rest of the mechanisms for treating missing information were comparable in frugality, placing between treating missing information as the



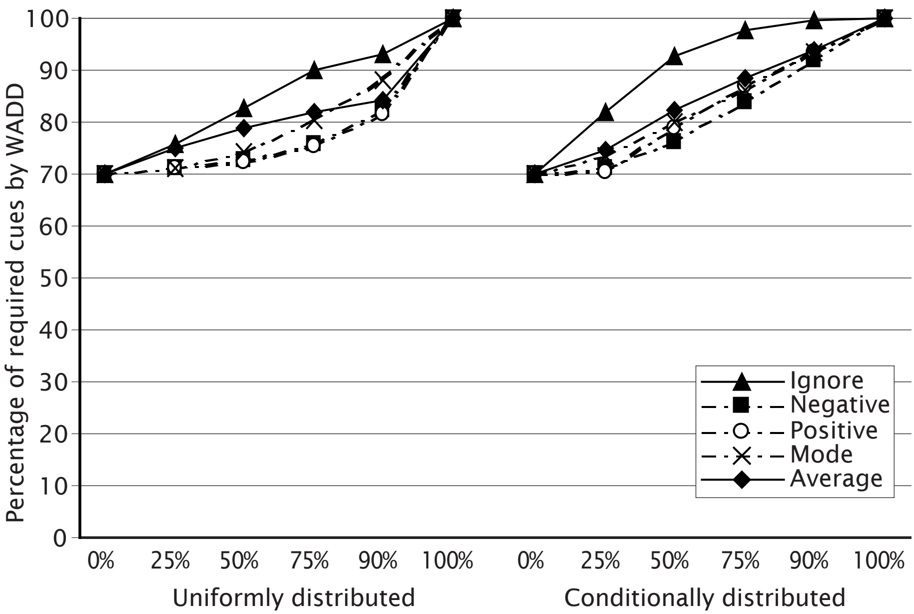


Figure 3. Average percentage of cues searched for by the five mechanisms for treating missing information when implemented in TTB (A) and WADD (B) across different levels of missing information (0 to 100%) when unknown cue values were uniformly distributed (left side) or conditionally distributed depending on the criterion value (right side).

average and ignoring missing information. Specifically, when treating missing information as negative, as positive, or as the mode, on average 53%, 55%, or 58% of the available information, respectively, were used. When more information was missing—that is, when missing information increased to 90%—the three mechanisms led to a frugality of 81%, 82%, and 88%, respectively.

In contrast, when WADD was selected, ignoring missing information was slightly less frugal than the rest of the mechanisms, which were comparable in the amount of required information. On average, ignoring missing information required 85% of the cues for WADD; however, when missing information was treated as negative, positive, the average, or the mode, 76%, 77%, 80%, or 79% of the cues, respectively, were used. Because WADD used almost all the available information, there was only a minor decrease in frugality when the amount of missing information increased. Furthermore, similar results, for both TTB and WADD, were obtained when missing information was uniformly or conditionally distributed in the environment.

Discussion

Previous research on human inferences with incomplete information has led to a mixed picture of how people treat missing information. The argument of the present research is that these mixed results can be explained by following a Brunswikian perspective—that is, by assuming that human judgments are to a large extent a reflection of the structure of the environment in which these judgments are made (Brunswik, 1943, 1956, 1957; Hammond, 1996). In other words, people will adaptively select a mechanism for treating missing information. Consequently, they will select the mechanism that leads to the highest accuracy. To support this argument, in a simulation study, the present experimenters analyzed whether the mechanism that leads to the highest inferential accuracy depends on the structure of the environment in which inferences are made.

The results illustrate that the implemented mechanism for treating missing information strongly influences the accuracy of different inference strategies. Which mechanism led to the highest accuracy crucially depended on the way missing information was distributed in the environment. Specifically, treating missing information as the average of the available information was most adaptive in terms of performance in environments with uniformly distributed missing information. In contrast, reacting to missing information as if it were negative was most adaptive when missing information was conditionally distributed depending on the criterion value. Ignoring missing information, however, did not lead to high inferential accuracy when compared with the other mechanisms. This result illustrates that the assumption of Gigerenzer et al. (1991) that missing information should be ignored is not adaptive in everyday inference problems. Therefore, forming expectations about missing information and using partial available information is better than simply relying on information that is known while ignoring what is missing. This result also calls into question Gigerenzer and Goldstein's (1996) assumption that treating missing information as negative is most adaptive, because it holds only in environments in which missing information is negatively correlated with the criterion value.

Even more important, the accuracy differences between the mechanisms for treating missing information were very large relative to the accuracy differences of the inferential strategies. This is a surprising empirical finding of the simulation study. Apparently, relying on the most valid cue, as practiced by the strategy TTB, is not outperformed by WADD, which integrates a large amount of information. Although a plausible assumption is that integrating almost all the available cues might lead to high accuracy, the additional information that WADD uses for making inferences has low predictive accuracy. Thus, WADD's advantage of compensating for the mistakes of single cues by the integration of other cues has the cost of relying on less valid information. Although these findings are surprising and new for the situation with missing information, they are in line with research that has studied the performance of these strategies in situations with complete information (see, for instance, Gigerenzer & Goldstein, 1996; Hogarth & Karelaia, 2007; or Juslin & Persson, 2002). From this result, a surprising conclusion can be drawn: To achieve high accuracy, selecting a good mechanism for treating missing information is more important than selecting the best inference strategy.

Another surprising result is that increasing amounts of missing information had very similar detrimental effects on the accuracy of TTB and WADD regardless of differences in frugality. Because WADD uses on average 80% of the available information to make an inference, the information that is present compensates for some information that is missing. In contrast, the lexicographic strategy TTB is much more frugal (i.e., on average, it uses 57% of the available information) and makes an inference on the basis of only one single cue. Consequently, the results of the present study support the view that it is adaptive to rely on high-validity cues even if they offer only partial information. Relying on additional but less valid cues does not increase the inferential accuracy.

When the amount of information a strategy required to make an inference was considered and the different mechanisms for treating missing information were implemented, the simulations offered a different picture. Specifically, treating missing information as the average led to the highest frugality when missing information was both uniformly and conditionally distributed in the environment. This mechanism led to more frequent discrimination between alternatives than the other mechanisms. However, this result holds only when TTB was selected as the inference strategy. Differences in frugality between mechanisms did not appear when they were implemented in WADD because it searches for most of the available information.

To achieve high inferential accuracy in environments in which missing information is uniformly distributed, unknown cue values should be treated as the average regardless of whether WADD or TTB is used. If information search costs are also crucial, people should always prefer TTB, since it requires less information than WADD, especially when missing information is treated as the average. In contrast, to obtain the highest accuracy in environments where missing information is negatively correlated with the criterion value, missing cue values should be treated as if they were negative. However, this mechanism requires more information than the treatment of missing information as the average. Here, decision makers need to trade off the higher accuracy achieved by treating missing information as negative against the costs of searching for more information. These conclusions about the adaptivity of different inference mechanisms should be tested experimentally in future research.

What happens if the distribution of missing information is unknown to the decision maker? The conclusions of the present study hold only when this distribution is known. In contrast, when confronted with a novel environment, the decision maker might not know anything about the distribution of missing information. In such a situation, treating missing information as the average appears most promising and adaptive, because it leads to the highest expected accuracy. Of course, if the missing information is, in fact, negatively or positively correlated with the criterion, treating missing information as negative or positive, respectively, would have been more adaptive.

When confronted with a novel environment, treating missing information initially as the average appears to be most adaptive. Treating missing information as the average would also lead to high frugality, especially when an inference strategy such as TTB is applied. However, such an initial way of treating missing information could then be revised when the decision maker acquires more knowledge about the environment. When the decision maker receives feedback about the correctness of the inferences, he or she can learn how missing information is distributed in the environment. As a consequence, instead of treating missing information as the average, the decision maker could switch to a more accurate way of treating missing information. An exciting question is whether people are able to show this adaptive behavior.

Previous research offers a rather mixed picture of how people handle missing information when making inferences. Some authors have argued that when decision alternatives are partially described, people treat missing information as if it were the average of the available information (e.g., Ganzach & Krantz, 1990; White & Koehler, 2004). Others have shown that people sometimes treat missing information as if it were negative (e.g., Huber & McCann, 1982; Jaccard & Wood, 1988). However, none of the authors has explained why people treat missing information differently. The results of the present study shed light on one of the factors that influences the accuracy of the different mechanisms for treating missing information and could possibly account for these mixed results: Which mechanism leads to the highest inferential accuracy depends on how the missing information is distributed in the environment. In some of the previous research, participants were possibly induced to believe that unknown cue values were negatively correlated with the criterion value. That is, cue values would be more likely to be missing for the alternatives with a low criterion value. As a consequence, participants might have treated missing information as if it were negative (see, for instance, Huber & McCann, 1982; Jaccard & Wood, 1988). Alternatively, in other experiments, participants could have assumed that missing information was uniformly distributed in the environment. In these cases, they might have treated unknown cue values as the average (see, for instance, Ganzach & Krantz, 1990; White & Koehler, 2004). The simulation results of this study provide theoretical context for future experiments on the topic. Still an open question and an avenue for future research is whether people are in fact able to select the mechanism for treating missing information adaptively when the distribution of unknown cue values is manipulated systematically.

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