Automatic and Controlled Components of Judgment under Uncertainty

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Abstract

The categorization of inductive reasoning into largely automatic processes (heuristic reasoning) and controlled analytical processes (rule-based reasoning) put forward by dual-process approaches of judgment under uncertainty (e.g., Stanovich & West, 2000) has been primarily a matter of assumption with a scarcity of direct empirical findings supporting it. We used the process dissociation procedure (Jacoby, 1991) to provide convergent evidence validating a dual-process perspective to judgment under uncertainty based on the independent contributions of heuristic and rule-based reasoning. Process dissociations based on experimental manipulation of variables were derived from relevant theoretical properties typically used to contrast the two forms of reasoning. These included processing goals (Experiment 1) and priming (Experiment 2). Results consistently supported the present perspective. We conclude that judgment under uncertainty is not either an automatic or controlled process, but that it reflects both processes, with each making independent contributions.

Keywords: Heuristics; dual process models; automatic processes; controlled processes; judgment under uncertainty.

Introduction

From our perspective, the greatest contribution of more than 30 years of research concerning the use of heuristics and biases is not so much the realization that intuitive judgments are often governed by heuristics that do not follow probability rules, but the revelation of a gap, within our own heads, between “natural assessments” such as availability or representativeness and the deliberate application of a justifiable set of inductive rules.

In recent years, dual-process approaches of judgment under uncertainty (e.g.,Kahneman & Frederick, 2002; Stanovich & West, 2000) have categorized the cognitive processes underlying inductive reasoning into two basic forms of reasoning: largely automatic associative processes, here referred to as *heuristic reasoning* (H) and controlled analytical processes, *rule-based reasoning* (RB).

But, *what* are these two forms of reasoning; *How* do they work; and *When* do they become active?

The *what* question: H refers to inferences based on simplifying principles such as similarity and contiguity, whereas RB refers to symbolically represented inferential rules structured by logic.

The *how* question: H operates intuitively in the sense that once triggered it gives rise to an autonomous process without further control until an end response pops out into consciousness. RB’s operation involves the deliberate application of rules that are put to work strategically according to the person’s goals.

The *when* question: H’s activation depends only on appropriate triggering cues (e.g., similarity matching involved in the representativeness heuristic), whereas RB’s activation depends on recognizing the applicability of an abstract rule (based on the verification of formal conditions), as well as on the availability of cognitive resources and motivation.

Research on judgment under uncertainty has traditionally employed errors and biases in answers to inferential problems to characterize the underlying heuristic principles and their consequences (e.g., Tversky & Kahneman, 1974). In such research, RB is typically gauged in terms of correct responses (defined by applicable probability or statistical rules) or calibrated responses (defined by ecological considerations or objective criteria) to inferential problems, while H is usually estimated by incorrect or badly calibrated responses to the same kind of inferential tasks.

This approach contrasts with our own both conceptually and methodologically. At the conceptual level, the above approach implies a zero-sum or hydraulic relation between the RB and the H process. As correct responses increase, incorrect responses necessarily decrease. Our dual-process approach conceives of the two processing modes as contributing independently to the judgment. At the methodological level, the above approach assumes that inferential problems or tasks are pure measures of underlying processes. However, such a process-pure assumption may be troublesome to maintain because tasks differ in a number of ways beyond the extent to which they tap H and RB. Rather, most, if not all, judgments under uncertainty will be influenced by simultaneously occurring heuristic and rule-based processes. Therefore, it is important to employ uncontaminated measures of processes through procedures that do not require or assume a one-to-one relation between tasks and processes. We employ one such solution by applying the process dissociation framework (Jacoby, 1991) to judgments under uncertainty.

Process Dissociation Procedure (PDP) and Judgments Under Uncertainty

The PDP was originally designed to separate automatic and conscious contributions to memory task performance (Jacoby, 1991). However, its logic may be applied to different experimental contexts as a general methodological tool for separating contributions of automatic and controlled processes. The procedure makes use of an inclusion condition where automatic and controlled processes act in concert, and an exclusion condition where the two processes act in opposition. Assuming that both processes contribute to performance and operate independently, estimates of each can be obtained by comparing performance across the two conditions.

Suppose you are asked to respond to the lawyer-engineer problem (Kahneman & Tverky, 1972). In this problem Dan is described by the psychologists who interviewed him as *conservative, careful, and ambitious* with *no interest in political issues and spending most of his free time on his many hobbies, which include carpentry, sailing, and mathematical puzzles.* Dan's description was drawn randomly from a set of descriptions that *included 30 engineers and 70 lawyers.* Which of the following is more likely? a) Dan is an engineer; b) Dan is a lawyer.

In this problem, Dan's description is closer to that of an engineer, but not highly diagnostically so. Thus, a judgment by representativeness (Kahneman & Tverky, 1972), based on the similarity between the description and the prototypes of engineer and lawyer, is in opposition to a response based on the application of a sampling rule (taking into consideration the prior probabilities of being an engineer or a lawyer). As such, choosing the response option "Dan is an engineer" is assumed to happen only if conscious application of a relevant inferential rule (C) fails and as a result of the automatic influences of heuristic processing: $A(1 - C)$. The lawyer-engineer problem, as well as other inferential problems possessing the same basic structure, may be considered good instantiations of an exclusion condition. However, one can also develop an inclusion condition for the same problem by simply inverting the base-rates. That is, you now consider a group of interviewees composed of 70 engineers and 30 lawyers. Therefore, the response option "Dan is an engineer" may be chosen as a consequence of using base-rates or simply because it was automatically computed as more similar to Dan's description. The proportion of responses "Dan is an engineer" is given by, $C + A(1 - C)$.

In sum, we begin with a dual-process approach to judgment under uncertainty that postulates the existence of two different processing modes, RB (involving explicit and controlled rule application) and H (based on automatic processing). We assume that RB and H processes operate in parallel and that they contribute to judgment independently of each other.

The Present Experiments

We report two experiments exploring how different independent variables influence RB and H. Each manipulation is historically relevant to the distinction between automatic and controlled processes. Our main goal is to determine whether derived estimates of RB and H will show expected trends based on our assumptions.

Literature involving judgments under uncertainty has traditionally assumed that performance based on H is unaffected by participants' intentions or goals (Sherman & Corty, 1984). Although some research has suggested that goals such as incentives to be accurate do not reduce heuristically driven biases (Camerer, 1987; Tversky & Kahneman, 1974), there is no direct evidence supporting this notion. Experiment 1 sought such evidence by manipulating participants' goals through instructions to answer the inferential problems in an intuitive or in a rational way. RB is believed to be under participants' control, whereas H is assumed to be largely automatic. Accordingly, varying participants' goals should affect RB but leave H unchanged.

Processing a particular stimulus in a particular way facilitates the subsequent repetition of the same processing with new stimuli (Smith, 1994). This facilitation is generally independent of any explicit memory of the previously presented stimuli. Accordingly, priming the use of heuristics is expected to dissociate the two reasoning modes by increasing H but leaving RB invariant. Experiment 2 primed participants with inferential problems designed to facilitate H highly similar to the target stimuli. On the other hand, RB was expected to be invariant because it corresponds to a reasoning mode governed by explicit application of rules, quite insensitive to the automatic processing principles underlying H.

Experiment 1

Participants The participants were 40 students (29 females and 11 males) at the University of Lisbon who participated in partial fulfilment of course requirements.

Procedure and Material For the experiments here reported, participants were given a brief oral introduction to the experiment on arrival at the laboratory. Written instructions followed by a list of problems were presented, and responses were collected on the computers. Each problem was followed by two response options. Participants had to choose one option before they could go on to the following problem.

In order to guarantee that participants never saw the inclusion and exclusion version of the same problem two lists of problems (list 1 and list 2) were created and manipulated between-participants such that inclusion problems in list 1 became exclusion problems in list 2 and vice versa. In each of these lists, problems were sorted differently to control for order effects. Order of presentation of the problems was random.

Two experimental conditions, corresponding to two instruction sets, were used in Experiment 1. In one condition, referred to as the intuitive condition, the experiment was introduced as a study of human intuition.

The study's goal was to evaluate personal intuition and sensibility when one has to make choices based on incomplete information. Participants were encouraged to base their answers to the problems on their intuition and personal sensitivity.

In the other condition, referred to as the rational condition, the experiment was introduced as a study on human rationality. The study's goal was to evaluate scientific reasoning ability when one has to make choices based on incomplete information. Participants were encouraged to behave like scientists, and to base their answers on rational and reflective thinking. Half of the participants were randomly assigned to each condition.

Problems used in Experiment 1 included base-rate problems, conjunction problems, and ratio-bias effect problems. Base-rate problems are equivalent to the classical lawyer-engineer problem (Kahneman & Tversky, 1972) but somewhat "easier". Base-rates used were more extreme and were expressed in absolute numbers (e.g., 85 lawyers and 15 engineers out of 100 persons). Individuating information was less diagnostic of a given category (e.g., engineer) than in the original problems. These changes allowed for a larger base-line of statistical answers when compared to the original problems.

Problems involving the conjunction rule appeared in a format not used in previous research. Participants were presented with two alternative solutions. The single case solution was associated with a certain probability of success, whereas the compound case solution involved two different stages with independent probabilities of success. Each one of these independent probabilities was higher than the probability of the single solution but the conjunction of the two was lower. For instance, one single agent can accomplish a certain activity within a specified time period with a probability of 60% (single case). Alternatively, two independent agents can divide that activity in two parts and finish them within a specified time period with probabilities of 70% and 80%, respectively (compound case). Note that the mean probability of success of the two agents is 75%, but the probability of both agents finishing their parts in time is only 56% (lower than the 60% probability of success of the single agent). If our participants consider only how large each independent probability is and neglect the consequences of set intersection (conjunction) for the compound case, this leads to a statistically incorrect answer.

The ratio-bias effect refers to the preference for equally small or even smaller probabilities for success when they are based on a larger sample size (Miller, Turnbull, & McFarland, 1989). For instance, Kirkpatrick and Epstein (1992) reported that 9 out of 100 is frequently preferred to 1 out of 10 probability of success, showing that this bias even extends to cases where the ratio of the larger sample actually represents a lower probability of success than the ratio of the smaller sample. In the ratio-bias effect problems used here, participants had to choose between two probabilities of success presented in the form of large and small samples. For the large samples, the absolute number of favorable cases is obviously larger than in the smaller samples. In the exclusion cases the smaller samples correspond to a higher probability of success.

In all these problems statistical response alternatives reflect "extensional" reasoning and non-statistical response alternatives (to exclusion problems) reflect "non extensional" reasoning. Extensional reasoning involves taking into consideration set inclusion and/or intersection (e.g., the consideration of base-rates, proportionality, conjunction, etc.). Non-extensional reasoning corresponds to the neglect of these problem features. (cf. Tversky & Kahneman, 1983).

All problems in Experiment 1 and 2 had an inclusion and an exclusion version. The exclusion versions (described above) correspond to the format traditionally used in research in judgments under uncertainty. The statistical and non-statistical answers correspond to alternative response options. The inclusion versions were the equivalent of exclusion versions except that the statistical information was inverted, so that both RB and H produced the same response option, the dominant response. In base-rate problems, base-rates and individuating information point to the same answer. In conjunction problems, the response option based on the conjunction of two items is not only less probable but also less representative than the single response option. In the ratio-bias effect problems, the larger sample is also a higher probability than the smaller one.

Data analysis of Experiment 1 considered participants' responses to 10 problems (5 base-rates problems, 2 conjunction problems, and 3 ratio-bias effect problems).

Dependent Measures To arrive at the H and RB estimates used as dependent measures, the proportions of non-statistical answers to exclusion problems and statistical answers to inclusion problems were obtained for each participant across problems and then used to compute individual RB and H estimates from PDP equations (Jacoby, 1991) presented below.

$$RB = P(\text{dominant answers}_{\text{inclusion}}) - P(\text{non-statistical answers}_{\text{exclusion}})$$

$$H = P(\text{non-statistical answers}_{\text{exclusion}}) / (1 - RB)$$

Estimation of the experimental parameters H and RB is dependent on a minimum level of errors in exclusion tasks. Perfectly statistical performance (i.e., no non-statistical answers to exclusion problems) mathematically constrains individual estimates of H to be zero ($H = 0/(1 - RB) = 0$). As a precaution, participants with zero non-statistical answers to exclusion problems were discarded for purposes of analyses (see Jacoby, Toth, & Yonelinas, 1993). Dependent measures for Experiment 2 were obtained in the same manner.

Design The Design is a 2 X 2 X 2 X 2 factorial with instructions type (intuitive and rational conditions), problem versions (list 1 and list 2), and problem order (list A and list B) between-subjects, and type of problem (inclusion and exclusion problems) within subjects.

Results Several separate one-way ANOVAs showed neither version effects nor order effects on the RB and H estimates.

The increase in the proportion of dominant answers (inclusion problems) and the decrease in non-statistical answers (exclusion problems) from the intuitive to the rational condition indicate that the instructions to consider the problems as a scientist have enhanced participants' performance (see table 1). An analysis of variance was performed with instruction type as a between-subjects factor and the RB and H estimates as repeated measures. The analysis revealed a reasoning mode main effect, indicating that H is greater than RB, $F(1,36) = 127{,}89$; $p = 0.00$ (MSE=0.04), and an instruction type X reasoning mode interaction, $F(1,36) = 3.75$, $p = .06$ ($MSE = 0.04$), reflecting the differential impact of instruction type on H and RB. Changing from "rational" instructions to "intuitive" instructions produced a strong reduction of RB, $t(36) = 2.02$, $p = .02$; $SD = 0.12$ (one-tailed planned comparisons), while leaving H constant, $t(37) < 1$; $SD = 0.05$ (two tailed planned comparisons)[1].

Discussion As predicted, RB was greater for rational instructions when compared to intuitive instructions, while H was largely unchanged across instructions sets. The invariance of H across instructions is in line with previous research on heuristics as natural assessments, showing heuristic-based reasoning to be insensitive to incentives to respond more thoroughly such as the use of pay-off matrices (e.g., Tversky & Kahneman, 1974).

To further test the independent contributions of H and RB to judgment it is crucial to show that, in contrast to Experiment 1's results, variables already known to affect automatic processes change H but left RB invariant. Priming effects have been investigated in judgment under uncertainty by varying the order in which more rule-based or heuristic perspectives are presented (e.g., Ginossar & Trope, 1987). In a related vein, Experiment 2 explored heuristic priming effects by manipulating the presentation of neutral versus heuristic priming problems.

Experiment 2

Participants The participants were 95 students (26 male students and 69 female students) at Indiana University who participated in partial fulfilment of course requirements.

Procedure and Material target problems were equivalent to the problems used in Experiment 1 except that conjunction problems were replaced by a new type of problem based on the law of large numbers (LLN). In the exclusion version of LLN problems, participants were asked to choose between two alternative response options, one of which was favored on the basis of a large sample (indicating statistical reasoning) and the other of which was favored by evidence from a much smaller sample (the choice of which would indicate non-statistical processing based on representativeness). In the inclusion versions of these problems, both H and RB processes favored the same option. The material also included heuristic priming problems, and neutral problems (used in the priming and control condition, respectively).

Besides sharing the same statistical principle as the target problems, heuristic priming problems were very similar to target problems in terms of their superficial structure (subject matter and story outline) within each problem's type. There are, however, two main differences between priming problems and target problems. First, priming problems do not have inclusion versions; they all are exclusion problems. Second, the target description information of priming problems is so diagnostic that, even in the face of opposing statistical information, the non-statistical response option is more appropriate than the statistical response option. As an example, consider a population that consists of 80 men and 20 women (high base-rate of men). One person is randomly chosen. This person likes modern art, is fashion aware, and breast fed the children. Is the person a woman or a man?

Table 1: Observed mean proportions of dominant answers (D) for inclusion problems and non-statistical answers (NS) for exclusion problems, and estimates of H and RB across priming and control conditions.

	Problem version		Estimates	
	Inclusion (D)	Exclusion (NS)	H	RB
Exp. 1				
Intuitive condition (n=19)	.69	.59	.70	.10
Rational condition (n=19)	.80	.47	.76	.33
Exp. 2				
Control condition (n=37)	.74	.42	.70	.32
Priming condition (n=40)	.83	.53	.83	.30

Despite the high base-rate of men, the description is even more diagnostic, and H-based judgments yield the better answer.

Neutral problems do not involve inductive reasoning, nor do they share similar superficial structures with priming and target problems. They are small texts followed by a question about mundane aspects of life. For instance, one neutral problem tells the story of Chad, who went to New York, loved it, but realized he would not like to live in such a big city. The following question was "Where would you prefer to live? a) In a big city like New York; b) In a small city like Bloomington."

[1] In the experiments here reported, it is hypothesized that the manipulations affect one of the reasoning modes in a given direction, leaving the other invariant. To test for these hypotheses, we used planned comparisons that are one-tailed tests for the changes of the reasoning mode estimates in the predicted direction, and two-tailed tests for the invariance of the other reasoning mode. In other words, the hypotheses receive empirical support if Ho is *rejected* in the first case and if Ho is *accepted* in the second case. To decrease the probability of committing a Type II error when *accepting* Ho, the value of α (probability of making a Type I error) is set to .1. Thus, when predicting change (one tailed tests), Ho will be rejected for $\alpha < .05$; when predicting invariance (two-tailed tests), Ho will be rejected for $\alpha < .1$.

Participants were randomly assigned to a priming condition or a neutral problem control condition. Problems were organized in four blocks, one for each type of target problem (base-rate problems, conjunction problems, ratio-bias effect problems, and problems based on the law of large numbers). In the priming condition, each block was composed of six priming problems followed by two target problems (one exclusion problem and one inclusion problem) that shared the same superficial features of the priming problems. The control condition was equivalent to the priming condition, except that priming problems were replaced by neutral problems. Data analysis considered participants' responses to 6 target problems (2 base-rate problems, 2 law of large numbers problems, and 2 ratio-bias effect problems).

Design The design is a 2 X 2 X 2 X 2 factorial with priming manipulation (heuristic priming and control condition), problem versions (list 1 and list 2), and problem order (list A and list B) between-participants, and type of problem (inclusion and exclusion problems) within participants.

Results Several separate one-way ANOVAs showed neither version nor order effects on the RB and H estimates.

In the heuristic priming condition, the proportion of both dominant answers for inclusion problems and non-statistical answers for exclusion problems increased (see table 1). An analysis of variance was performed, with heuristic priming as a between-subjects factor and RB and H estimates as repeated measures. The analysis revealed a reasoning mode main effect, indicating that H is greater than RB, $F(1,75)$ = 163,69 (MSE=0.05); p = 0.00, and a heuristic priming X reasoning mode interaction, $F(1,75) = 3.87$; $p = .05$ (MSE = 0.05). Planned comparisons indicated that priming H produced an increase in H, $t(75) = 2.278$, $p = .01$; $SD = 0.24$ (one-tailed) while leaving RB largely unchanged, $t(75) < 1$; $SD = 0.18$ (two-tailed planned).

Discussion As predicted, heuristic priming problems with highly similar superficial structures to the target problems facilitated subsequent H processes without affecting RB.

Heuristic priming seems to be an effective way to increase H. The individuating information of the target problems used in the present experiments was less diagnostic than in the original problems used by others (e.g., Tversky & Kahneman, 1974). It is likely that, at least for some participants, this individuating information was not diagnostic enough to trigger the automatic associative process that characterizes H. Thus, Experiment 2's priming manipulation increased H's activation level enough so as to augment heuristic-based responses to subsequent target problems that had weak individuating information. The same priming manipulation did not affect RB because this reasoning mode is a deliberate activity governed by cognitive representations of inductive rules and is not based on the automatic processing principles underlying H.

General Discussion

Judgment under uncertainty has recently been approached from the perspective of dual-process models (e.g., Kahneman & Frederick, 2002; Stanovich & West, 2000). These models converge in postulating that inductive judgment may be based on heuristic (H) and/or on analytical (RB) processing modes.

According to these models, H, as a largely automatic, fast, and effortless process, consists of the spontaneous activation of simplifying principles such as similarity and temporal structure (e.g., the representativeness heuristic). In contrast, RB is a controlled process involving the intentional and effortful activation of a sequence of symbolically represented information (inductive rules).

The above characterization of H and RB has been mostly a matter of assumption, with surprisingly little direct empirical support. The work reported here intended to change this state of affairs. Specifically, we used the PDP to assess both H and RB and to demonstrate theoretically derived process-dissociations. The experiments showed that variables traditionally associated with controlled processes such as processing goals (experiment 1) affected RB but not H processes. Conversely, a variable already known to affect automatic processes such as procedural priming (Experiment 2) affected H but left RB unchanged. The process dissociations obtained across the two experiments support the proposal that automatic versus controlled processes in judgments are not an either/or proposition but rather that both operate in an independent and parallel way. In addition, the results demonstrate that simply assessing statistical or non-statistical responses can not reveal the level of rational or heuristic processing.

Past research found greater attention to base-rates when participants were instructed to think like scientists (Zukier & Pepitone, 1984) and greater use of base-rates to the extent that it was instrumental to reach previously defined goals (Ginossar and Trope (1987). Experiment 1's results suggest that these effects are independent of H and are exclusively due to an increase in RB.

A number of dual-process models have argued that heuristic and rule-based processes represent distinct alternatives and that the processes do not co-occur (e.g., Kahneman & Tversky, 1973). Other models (e.g., Fiske & Neuberg, 1990) have argued that RB and H represent two ends of a continuum, and that movement toward one end of the continuum necessarily coincides with diminished activity on the other end. In contrast, the PDP approach assumes that all judgments reflect the joint and independent contributions of RB and H. Increases in one process do not imply decreases in the other. Other dual-process models do emphasize the simultaneous influences of heuristic and systematic processes both in judgment under uncertainty (e.g., Kahneman & Frederick, 2002) and in reasoning (e.g., Evans & Over, 1996; Johnson-Laird et al., 1999). However, only the PDP approach also offers a means for independently assessing the joint contributions of these processes to performance on a single task.

The use of the PDP experimentally constrains the automatic nature of H, defining it by the relation between performance in inclusion problems and that in exclusion problems. As a consequence, to be automatic, H must have an obligatory nature in that it remains the same regardless of whether its influence facilitates or hampers performance. Other uses of the term “heuristic reasoning” that does not accommodate this conception of automaticity refer to reasoning forms that could not be separated from (controlled) RB using the PDP and as such are beyond the scope of the present definition of H. Other dual-process approaches to reasoning adopt a conception of automaticity that is similar to our own (Kahneman & Frederick, 2002; Stanovich & West, 2000). On the other hand, since RB does not capture all forms of rule-governed cognitive activity but only the deliberate use of certain statistical principles, other controlled processes not anticipated by us may have also contributed to the dominant answers to inclusion problems and non-statistical answers to exclusion problems. Nevertheless, a nonrandom distribution of such types of bias would certainly affect the PDP estimates, rendering findings of invariance highly unlikely.

In the PDP model applied here (Jacoby, 1991), the RB process constrains the influence of the H process. That is, the equations are such that the influence of H will be observed only in cases in which RB does not provide a response. However, it is clear that automatic and controlled processes do not always interact in this C-first fashion. Instead, in some cases, it will be the automatic process that dominates and constrains the application of control. For example, on incompatible trials in the Stroop Task (i.e., the word Blue written in red ink), the automatic habit to read the word captures attention and interferes with the more controlled process of naming the color of the ink (see Lindsay & Jacoby, 1994 for an A-first application of the PDP). Since the C-first model has consistently provided a better account of results than the A-first model, it is the C-first analyses that are reported here. It is important to note that, although the choice of which model to apply was an empirical one, that choice did constrained subsequent interpretation of our data.

In applying the PDP to inductive judgment, the present work aims to contribute a clearer definition of the automatic and intentional processes involved in inductive judgment. In essence, the resulting dual-process approach explores the operating principles and representational nature of human inferences in light of advances in the social cognitive literature toward a better and more articulated comprehension of judgments under uncertainty. This work is far from being completed.

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References

Camerer, C. F. (1987). Do bias in probability judgment matter in markets? Experimental evidence. *American Economic Review, 77*, 981-997.

Evans, J. St. B. T. & Over, D.E. (1996). Rationality and Reasoning. Hove, UK; Psychology Press.

Fiske, S. T., & Neuberg, S. E. (1990). A continuum of impression formation, from category-based to individuating processes: Influences of information and motivation on attention and interpretation. In M. P. Zanna (Ed.), Advances in experimental social psychology (Vol. 23, pp. 1_74). San Diego, CA: Academic Press.

Ginossar, Z., & Trope, Y. (1987). Problem solving in judgment under uncertainty. *Journal of Personality and Social Psychology, 52,* 464-474.

Jacoby, L. L. (1991). A process dissociation framework: Separating automatic from intentional uses of memory. *Memory and Language, 30,* 513-541.

Jacoby, L. L., Toth, J. P., & Yonelinas, A. P. (1993). Separating conscious and unconscious influences of memory: Measuring recollection. *Journal of Experimental Psychology: General, 122,* 139-154

Johnson-Laird, P.N., Legrenzi, P., Girotto, V., Sonino-Legrenzi, M. &Caverni, J-P. (1999). Naive probability: A mental model theory of extensional reasoning. Psychological Review, 106 (1), 62-88

Kahneman, D., & Frederick, S. (2002). Representativeness revisited: Attribute substitution in intuitive judgment. In T. Gilovich, D. Griffin, & D. Kahneman (Eds.), *Heuristics and biases: The psychology of intuitive judgment*. Cambridge: Cambridge University Press.

Kahneman, D., & Tversky, A. (1972). Subjective probability: A judgment of representativeness. *Cognitive Psychology, 3,* 430-454.

Kahneman, D., & Tversky, A. (1973). On the psychology of prediction. *Psychological Review, 80,* 237-251.

Kirkpatrick, L. A., & Epstein, S. (1992). Cognitive-experiential self-theory and subjective probability: Further evidence for two conceptual systems. *Journal of Personality and Social Psychology, 63,* 534-544.

Lindsay, D. S., & Jacoby, L. L. (1994). Stroop process-dissociations: The relationship between facilitation and interference. *Journal of Experimental Psychology: Human Perception and Performance, 20,* 219-234.

Miller, D. T., Turnbull, W., & McFarland, C. (1989). When a coincidence is suspicious: The role of mental simulation. *Journal of Personality and Social Psychology, 57,* 581-589.

Sherman, S. J., & Corty, E. (1984). Cognitive heuristics. In R. S. Wyer & T. K. Srull (Eds.), *Handbook of social cognition* (Vol. 1). Hillsdale, NJ: LEA.

Smith, E. R. (1994). Procedural knowledge and processing strategies in social cognition. In R. S. Wyer & T. K. Srull (Eds.), *Handbook of social cognition* (Vol. 1). Hillsdale, NJ: Lawrence Erlbaum Associates.

Stanovich, K. E., & West, R. F. (2000). Individual differences in reasoning: Implications for the rationality debate. *Behavioral and Brain Sciences, 23,* 645-665.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science , 185,* 1124-1131.

Tversky, A., & Kahneman, D. (1983). Extensional versus intuitive reasoning: The conjunction fallacy in probability judgment. *Psychological Review, 90,* 293-315.

Zukier, H., & Pepitone, A. (1984). Social roles and strategies in prediction: Some determinants of the use of base-rate information. *Journal of Personality and Social Psychology, 47,* 349-360.