Title
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Automatic and Controlled Components of Judgment and Decision Making

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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., K. E. Stanovich & R. F. West, 2000) has been primarily a matter of assumption with a scarcity of direct empirical findings supporting it. The present authors use the process dissociation procedure (L. L. 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 the most relevant theoretical properties typically used to contrast the two forms of reasoning. These include processing goals (Experiment 1), cognitive resources (Experiment 2), priming (Experiment 3), and formal training (Experiment 4); the results consistently support the author's perspective. They conclude that judgment under uncertainty is neither an automatic nor a controlled process but that it reflects both processes, with each making independent contributions.

Keywords: dual-process approach, heuristic reasoning, rule-based reasoning, process dissociation

Think for a moment about all of the relevant factors involved in daily judgments such as the likelihood of a current relationship leading to marriage or a sports team winning a game. This mental experience is usually enough to make us aware of the simple fact that the world is too complex to predict accurately. Perhaps we can rely on resource-consuming decision rules based on formal theories of probability, but even those may be unsatisfactory and are not always consensual. Of course, they do often work and lead to accurate judgments. Alternatively, instead of the deliberate use of algorithms, sometimes a judgment or prediction seems to come to us, rather spontaneously and quickly, and a feeling of relative certainty (or uncertainty) will "pop-out." Even when basing judgments on such a simple process, we sometimes make probability judgments that are relatively well calibrated. In addition, the two kinds of judgment processes often occur together. When they suggest the same answer, there is no problem or conflict. However, a good deal of tension and anxiety may come about when deliberate rule-based reasoning and intuitive heuristics produce contradictory outputs within our own heads.

For example, it is quite trivial to calculate that the likelihood of picking the one red ball in an urn out of 10 balls is 10% and that the likelihood of picking a red ball from another urn when there are 8 red balls out of 100 is only 8%. Yet, even knowing this, when we are asked from which urn we would prefer to sample and try to get a red ball and win $100, many of us have a compelling desire to choose the urn with 100 balls (and in fact, do make such a choice if asked to use their gut feelings), despite the fact that we "know" this is an irrational choice (Denes-Raj & Epstein, 1994). Similarly, even though we know rationally that the two lines in the Müller-Lyer illusion are the same length, we cannot escape the feeling, and the perception, that they are different. Some judgments seem to come to us (and stay with us) independently of any logical considerations.

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 it is 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., Chaiken & Trope, 1999; Kahneman & Frederick, 2002; Kirkpatrick & Epstein, 1992; Sloman, 1996; Sloman & Rips, 1998; 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]).[1] Although this characterization has led to several property lists contrasting the two reasoning modes (Sloman, 1996; Smith & DeCoster, 1999; Stanovich & West, 2000), such theoretical descriptions have been primarily a matter of assumption with a scarcity of direct empirical findings supporting it. In this article, we report theoretically based process dissociations between the two forms of reasoning, obtained by experimentally manipulating variables derived from the most relevant theoretical properties typically used to contrast the two forms of reasoning. As Kahneman (2003) has noted: "There is considerable agreement on the characteristics that distinguish the two types of cognitive processes" (p. 698). Answering the what, how, and when of H and RB seems a sensible starting point to describe the general view that has motivated most dual-model research in reasoning and decision making. In other words, what are these two forms of reasoning? How do they work? W*hen* do they become active?

The what: 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: 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: 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.

The Dual Nature of Judgment Under Uncertainty

A successful account of judgment under uncertainty must be capable of retaining the explanatory power of the past research on simplified heuristics and biases (for reviews see Kahneman, Slovic, & Tversky, 1982; Sherman & Corty, 1984), but it must also be able to delineate the conditions underlying inductive judgment based on deliberate RB (e.g., Fong, Krantz, & Nisbett, 1986). Thus, we argue that human inductive reasoning has a dual nature: one aspect operates by heuristic principles such as similarity and contiguity, and the other operates by the use of deliberate analytic rules (Sloman, 1996; Smith & DeCoster, 1999). Such an approach describes several existing dual-process models of judgment under uncertainty (Epstein, 1994; Griffin, Gonzalez, & Varey, 2001; Kahneman & Frederick, 2002; Stanovich & West, 1999, 2000). However, none of these models has attempted to derive, in the area of reasoning under uncertainty, independent estimates of these two processes and to observe independent effects of manipulated variables on the two processes. Such evidence would clearly demonstrate the dual-process nature of judgments under uncertainty.

The successful modeling of dual-process approaches typically involves two steps. First, one must establish a one-to-one relation between processing modes and participants' responses to inferential tasks. That is, the adoption of the H process must be associated with a particular response, and the adoption of the RB process must be associated with a particular response. Second, one must demonstrate and understand how empirical variables selectively affect the two processes.

Research on judgment under uncertainty has traditionally used errors and biases in answers to inferential problems to characterize the underlying heuristic principles and their consequences (Kahneman & Tversky, 1972, 1973; Tversky & Kahneman, 1971, 1973, 1974). However, researchers readily note that, although heuristics play a major role in judgment, reasoning based on the purposeful application of some statistical concepts is also a part of people's judgmental repertoire (e.g., Ginossar & Trope, 1987; Jepson, Krantz, & Nisbett, 1983; Kruglanski, Friedland, & Farkash, 1984; Nisbett, Krantz, Jepson, & Kunda, 1983). 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, whereas associative inferential processes (H) are usually estimated by incorrect or badly calibrated responses to the same kinds 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 processes. 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 (rule-based and associative processes, respectively). 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 automatic (heuristic) versus controlled (rule-based) processes. In the same vein, different levels of a manipulated variable may differ in ways other than simply mapping onto RB and H. Several lines of research have led to the conclusion that there is often not a sharp dissociation between analytic and heuristic reasoning (Ajzen, 1977; Bar-Hillel, 1979, 1980; Tversky & Kahneman, 1974, 1982).

The more general point is that no task is "process pure." An inferential task that depends entirely on heuristic processes and not at all on rule-based processes is technically unattainable. An inferential task that depends entirely on rule-based processes and not at all on heuristic processes is highly unlikely. Rather, most, if not all, judgments under uncertainty are influenced by simultaneously occurring heuristic and rule-based processes. The process-pure problem is present, to a smaller or greater extent, in research involving other variables that are known to affect respondents' performance on inferential tasks such as time available for deliberation (Finucane, Alhakami, Slovic, & Johnson, 2000), intelligence (Stanovich & West, 1998, 2002), mood (Bless & Schwarz, 1999), opportunities to apply intuitive representations of statistical rules (Ginossar & Trope, 1987), presentation format (Gigerenzer, 1991; Tversky & Kahneman, 1983), and perceptual salience of randomness (Ferreira & Garcia-Marques, 2003).

The process-pure problem is not specific to the study of inferential processes, but it emerges whenever processes are to be measured in terms of particular experimental tasks (Hollender, 1986; Jacoby, 1991). As a consequence, selective influences of

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[1] We consider heuristic reasoning to be based on natural associative assessments such as similarity matching (representativeness) and memory fluency (availability). We also recognize that some heuristics involve meta-cognitive activity (e.g., the ease-of-retrieval heuristic) that reflect judgments about the validity of activated associations rather than associative processes per se. Both involve automatic rather than reasoned, analytic processes. In our studies, the heuristics do involve associative processes (see our subsequent definitions of H and RB), and we thus use the term *associative* in describing heuristic reasoning.

empirical variables cannot be measured directly. Therefore, it is important to use uncontaminated measures of processes through procedures that do not require or assume a one-to-one relation between tasks and processes. We use one such solution by applying the process dissociation framework 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 a facilitation paradigm or inclusion condition in which automatic and controlled processes act in concert and an interference paradigm or exclusion condition in which 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.

Consider a fame judgment task in which you are asked to study a list of names (Jacoby, Kelley, Brown, & Jasechko, 1989). At test you are presented with another list of names, half of which have been included in the study list (old), and the other half of which are new. In the inclusion condition you are told to decide whether each name is of a famous or a nonfamous person. Furthermore, you are informed that all the names included in the study list were of famous persons. Thus, if you happen to remember that a name was included in the study list, you should judge it to be of a famous person. Some names may also simply "sound" familiar even if you don't remember whether they were included in the study list or not. In such cases, old names judged as famous may have been consciously recollected (C) or they may have come to mind automatically (A). The probability of judging an old name as famous is given by: $C + A(1 - C)$. In this case, the use of either process would lead to the same result. In the exclusion condition, you are told to decide whether each name is of a famous or a nonfamous person, and you are further informed that all the names included in the study list were of nonfamous persons. Thus, if you happen to remember that a name was included in the list, you should judge it to be of a nonfamous person. In such a case, judging an old name as famous would happen only if conscious recollection failed and as a result of automatic influences of memory: $A(1 - C)$. In this case, the two processes work in opposition to each other. Given these two equations, one can derive estimates of automatic and controlled processes. The difference between performance in the inclusion and exclusion conditions provides an estimate of C (C = Inclusion–Exclusion); similarly the estimate of the automatic component can be obtained in the following way: $A = \text{Exclusion}/(1 - C)$.

Now, suppose you are asked to respond to the following version of the lawyer–engineer problem (Kahneman & Tverky, 1972):

> Several psychologists interviewed a group of people. The group included 30 engineers and 70 lawyers, The psychologists prepared a brief summary of their impression of each interviewee. The following description was drawn randomly from the set of descriptions: Dan is 45. He is conservative, careful, and ambitious. He shows no interest in political issues and spends most of his free time on his many hobbies, which include carpentry, sailing, and mathematical puzzles. 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; Tversky & Kahneman, 1971), 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 (opposing heuristic and rule-based judgments), may be considered good instantiations of an interference paradigm or exclusion condition. However, one can also develop an inclusion condition for the same problem. An easy way to obtain such an inclusion version of the above lawyer–engineer problem is to simply invert 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 applying a sampling rule by 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 most judgment research, the problems that are used are almost always exclusion problems. That is, the rule-based and the automatic processes lead to different responses. However, as in the lawyer–engineer problem above, it is possible to develop inclusion versions very similar to the original versions (exclusion versions) except that rule-based and heuristic judgments coincide in leading to the same response output. Once one develops comparable inclusion and exclusion conditions, it is possible to apply the logic of the PDP to obtain separate estimates of RB and H.

As indicated, 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

The PDP provides a way to investigate theory-driven process dissociations underlying the current approach to reasoning under uncertainty. We report four experiments exploring how different independent variables influence the estimates of 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 (but not based on RB) is unaffected by participants' intentions or goals (Kahneman & Frederick, 2002; 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.

One of the main reasons usually put forward for the ubiquitous use of H in everyday inductive judgments is its efficiency. In contexts of high cognitive load, the use of heuristics produces fast and effortless responses that often conform to the outcome of deliberate and effortful statistical judgments (RB). If the characterization of H and RB processes in terms of their demand of cognitive resources is accurate, then manipulations of cognitive load to induce simple or resource-demanding processing (e.g., Chen & Chaiken, 1999) should dissociate the two processing modes. Experiment 2 places some participants under a cognitive load, and this depletion of attentional resources is expected to decrease RB but to leave H estimates largely invariant.

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 3 primed participants with inferential problems designed to facilitate H. In addition, the priming problems in Experiment 3 and the subsequent target problems shared the same superficial structure and were presented sequentially. Because H reasoning is often based on associative assessments of similarity, the use of highly similar problems for priming and target stimuli should also facilitate H. On the other hand, RB processes were expected to be invariant because they correspond to a reasoning mode governed by explicit application of rules, largely insensitive to the automatic processing principles underlying H.

In contrast, priming of rule-based processing should affect the subsequent use of RB but leave H unaffected. In fact, the mere induction of formal thought has been shown to generally improve subsequent measures of abstract reasoning (e.g., LaRue & Olejnik, 1980). As a case of abstract reasoning, RB should be responsive to formal training. In contrast, given its heuristic nature and the considerable degree of independence between the two processing modes, H is expected to be insensitive to any rule-governed formal activity prior to an inferential task. Experiment 4 primed participants with formal rule-based problems before they responded to subsequent target problems. The induction of formal thought was expected to increase RB processes but have no effect on H.

Experiments 1, 2, 3, and 4 were thus designed to validate the PDP as a suitable method to study heuristic and rule-based processes underlying judgments under uncertainty and to provide evidence for the simultaneous operation of both RB and H. More important, they directly test a number of predictions logically derived from the literature on judgments under uncertainty (Epstein, 1994; Kahneman & Frederick, 2002; Sloman, 1996; Stanovich & West, 1998, 2002) that, to our knowledge, have received no direct empirical support to date.

Experiment 1

In Experiment 1, we obtained estimates of RB and H for participants' performance under two different processing goals. Specifically, goals were manipulated through instructions to answer a set of inclusion and exclusion problems in an intuitive way or to answer it in a more reflective way. Given RB's controlled and intentional nature and H's autonomous and more spontaneous nature, RB is expected to be greater when participants are given reflective instructions compared with when they are given intuitive instructions. Because H processes are automatic and unaffected by goals, H is expected to be largely unchanged across the instructions sets.

Method

Participants. The participants were 40 students (29 women and 11 men) at the University of Lisbon who participated to fulfill a requirement of their introductory educational psychology course.

Procedure and material. For Experiment 1, and for the rest of the experiments here reported, participants were given a brief oral introduction to the experiment on arrival at the laboratory, and they were then escorted to a room equipped with PC-compatible computers. Experimental sessions comprised between 1 and 6 participants. 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. They responded to the problems at their own pace and waited in their places until everyone in their session had finished.

In all four experiments, two lists of problems (List 1 and List 2) were created such that inclusion problems in List 1 became exclusion problems in List 2 and vice versa. In order to guarantee that participants never saw the inclusion and exclusion version of the same problem, List 1 and List 2 were manipulated between participants. In each of these lists, problems were sorted differently to control for order effects, leading to Lists 1A and 1B and Lists 2A and 2B, respectively. Order of presentation of the problems was random with the restriction that not more than two problems of the same version type or involving the same statistical principle could be presented in a row.

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 on the basis of 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 on the basis of 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 the intuitive condition and the other half to the rational condition.

Problems used in Experiment 1 include base-rate problems, conjunction problems, and ratio-bias effect problems. Base-rate problems are equivalent to the classical lawyer–engineer problem (Kahneman & Tversky, 1972). Specifically, participants have to choose between two opposing response options, one that is favored by the base rates (reflecting rule-based processing) and the other that is favored by the description of the target (reflecting heuristic processing). The base rates used were more extreme than in the original Kahneman and Tversky (1972) problems and were expressed in absolute numbers instead of percentages (e.g., 85 lawyers and 15 engineers out of 100 persons). Furthermore, individuating information was less diagnostic of a given category (e.g., engineer) than in the original problems, and the stories always made explicit reference to some kind of random process by which the target individual (the specific person described in the problem) was chosen.[2] These changes gave rise to equivalent but "easier" base-rate problems, allowing for a larger proportion of statistical answers when compared with 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 probabil-

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[2] By mistake, the reference to the random process was omitted in one of the base-rate problems.

ity 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. On the contrary, the consideration of the relative magnitude of the intersection between the two sets considered in the compound case leads to the statistically correct answer.[3]

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 (Kirkpatrick & Epstein, 1992; Miller, Turnbull, & McFarland, 1989). For instance, there is a tendency to intuitively prefer a probability of success of 10 out of 100 when compared with 1 out of 10. The higher absolute number of favorable cases in the first ratio renders it more attractive. 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 in which 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. However, in the exclusion cases the smaller samples correspond to a higher probability of success.

In past work applying the PDP, the response based on RB in the exclusion version is the correct response. The response based on H in the exclusion version is the incorrect response. The designation of correct and incorrect for RB and H responses makes sense for previous studies that investigated memory (Jacoby, 1991), fame judgments (Jacoby et al., 1989), Stroop task responses (Lindsay & Jacoby, 1994), or stereotypes (Payne, 2001). In all of these cases, responses based on RB are in fact the correct ones. In the present studies, the designation of correct and incorrect for the exclusion problems is not so clear. For some of the problems (the ratio-bias effect problems), the RB response is the correct response. Two of 10 envelopes (the response based on the RB process) gives one a better chance of winning than 19 of 100 (the response based on the H process). For other problems, the correct response is indeterminate. For example, in the base-rate problems, whether the base-rate derived response (the RB response) is correct depends on the real or perceived diagnosticity of the information that describes the social target. If that information is highly diagnostic, the H response may in fact be more likely to be correct. However, in the decision-making arena, there is a clear difference between statistically based (RB) problem solving and judgmental heuristics (H). To be precise, statistical response alternatives (to exclusion problems) reflect *extensional reasoning* and nonstatistical response alternatives (to exclusion problems) reflect *nonextensional reasoning*. Extensional reasoning involves taking into consideration set inclusion and/or intersection (e.g., the consideration of base rates, proportionality, conjunction). Nonextensional reasoning corresponds to the neglect of these problem features (cf. Tversky & Kahneman, 1983). Note that taking extensional features into account does not necessarily guarantee a normatively suitable answer.

For ease of presentation (and in the absence of more clear nomenclature), we refer to responses reflecting RB and H in the exclusion problems as *statistical* and *nonstatistical* responses, respectively. The PDP is applicable whether or not there is a clear correct response, so long as RB and H lead to the same response in the inclusion version and to different re-

sponses in the exclusion version. We return to this issue in the presentation of Experiment 3.

All problems in Experiment 1 (and in the other experiments) had an inclusion and an exclusion version. The exclusion versions or exclusion problems (described in the preceding paragraph) correspond to the format traditionally used in research in judgments under uncertainty. It is customary in these problems that the statistical and nonstatistical answers correspond to different responses or alternative response options.

The inclusion versions (or inclusion problems) 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.[4] Nondominant responses to inclusion problems do not correspond to either RB or H reasoning. Instead, they are likely to be based on some other kind of idiosyncratic associations (e.g., *I have a cousin named Dan, and he is a lawyer*).

The dominant answers in the inclusion version of a given problem correspond to the added contribution of H and RB processes, whereas the statistical answers to the exclusion version of the same problem reflect only the RB contribution. Therefore, the proportion of dominant answers in the inclusion version should be greater than the proportion of statistical answers in the exclusion version. Problems were pretested and selected to meet this criterion.

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 nonstatistical answers to exclusion problems and dominant answers to inclusion problems were obtained for each participant across problems and were then used to compute individual RB and H estimates from PDP Equations 1 and 2 (Jacoby, 1991):

$$RB = P(\text{dominant answers}_{\text{inclusion problems}})$$
$$- P(\text{nonstatistical answers}_{\text{exclusion problems}}), \quad (1)$$

$$H = P(\text{nonstatistical answers}_{\text{exclusion problems}})/(1 - RB). \quad (2)$$

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[3] We also used traditional conjunction problems similar to the "Linda problem" (Tversky & Kahneman, 1983). However, for these problems we did not accurately follow the logic of opposition underlying the PDP. An important assumption of the PDP approach is that levels of controlled and automatic processes do not change across inclusion and exclusion conditions (Jacoby, 1991; Jacoby, Toth, & Yonelinas, 1993). The logic is that the H process always works in the same direction with the same strength (although leading to correct answers on inclusion trials and incorrect answers on exclusion trials). The RB process should work in opposite directions for the inclusion and exclusion cases but should have equal strength in the two cases. All our problems except the Linda-type problems follow this logic. For those problems, it was RB that worked in the same direction for the inclusion and exclusion cases, and H that led to different answers in the two cases. In these cases, we cannot guarantee that H operates with the same strength across inclusion and exclusion problems only in different directions. Thus, the PDP assumption that H (and RB) contributions are equally strong in inclusion and exclusion trials is likely to be violated. In light of this, we discarded responses to conjunction problems of this type in the data analyses. Such conjunction problems were eliminated from consideration in all four experiments. We thank Larry Jacoby for calling our attention to this point.

[4] See Appendix A for examples of target problems used in Experiments 1, 2, and 4.

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 nonstatistical answers to exclusion problems) mathematically constrains individual estimates of H to be zero (H = 0/[1 − RB] = 0). As a precaution, participants with zero nonstatistical answers to exclusion problems were discarded for purposes of analyses (see Jacoby, Toth, & Yonelinas, 1993). Dependent measures for Experiments 2, 3, and 4 were obtained in the same manner. This issue will be addressed in the General Discussion.

Design. The design is a 2 × 2 × 2 × 2 factorial with instruction type (intuitive and rational conditions), problem version (List 1 and List 2), and problem order (List A and List B) as the between-subjects variables and type of problem (inclusion and exclusion problems) as the within-subjects variable.

Results

Several separate one-way ANOVAs showed neither version effects nor order effects on the RB and H estimates. Therefore these results are not discussed further. H and RB estimates across intuitive and rational conditions are shown in Table 1.

The increase in the proportion of dominant answers (inclusion problems) and the decrease in nonstatistical 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. An ANOVA was performed with instruction type as a between-subjects variable and the RB and H estimates as repeated measures. The analysis revealed a reasoning mode main effect, indicating that H is greater than RB, $F(1, 36) = 127.89$, $MSE = 0.04$, $p = .00$, and an instruction Type × Reasoning mode interaction, $F(1, 36) = 3.75$, $MSE = 0.04$, $p = .06$, reflecting the differential impact of instruction type on H and RB. Changing from "rational" instructions to "intuitive" instructions produced a strong reduction of RB, $t(36) = 2.02$, $SD = 0.12$, $p = .02$ (one-tailed planned comparisons), while leaving H constant, $t(37) < 1$, $SD = 0.05$ (two-tailed planned comparisons).[5]

Discussion

Experiment 1 examined the impact of processing goals on the contributions of RB and H to inductive judgment tasks. Participants were instructed to answer a set of inclusion and exclusion problems in an intuitive way or to answer them in a more reflective way. Given RB's controlled and intentional nature and H's spontaneous nature, we predicted that RB would be greater for rational instructions when compared with intuitive instructions, whereas because H is an automatic process unaffected by goals, we pre-

dicted that it would be largely unchanged across instructions sets. Results corroborated our hypotheses. 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).

Experiment 2

In Experiment 1, we explored the impact of intentional goals on RB and H by obtaining process-dissociation estimates of the two reasoning modes. In Experiment 2, we examined the effect of cognitive load on both processes as another way to dissociate H from RB. Automatic processes such as H should be unaffected by the depletion of attentional resources under cognitive load. In contrast, given its resource demanding nature, RB should compete for cognitive resources with a digit rehearsal task, resulting in a decrease of RB estimates.

Method

The inductive judgment task of Experiment 2 was memory-based. That is, the question for each problem did not directly follow the problem's text. Instead it was delayed in time and appeared later when the problem's text was no longer available. Thus, participants initially read a problem, but no question was asked. Only afterwards, when the problem's text was no longer available, did participants respond to the question. Therefore, participants' responses were based on their memory of the problems. A second memory task competed with the judgment task for cognitive resources. Participants were asked to memorize a number and keep rehearsing it while choosing one of the two response options. The cognitive load conditions differed in the length of the number to be rehearsed (one-digit or seven-digit numbers).

Participants. The participants were 112 students at Indiana University who participated to partially fulfill a requirement of their introductory psychology course. They were randomly assigned to one of the experimental conditions.

Procedure and material. After the initial instructions, participants began by reading a problem displayed on the computer screen. When finished, they pressed a "continue" key and proceeded to a second screen, which presented a number (consisting of either one or seven digits) with instructions to memorize it. Numbers were displayed for a 5-s period. The following screen displayed the problem's corresponding question with two alternative response options. Participants were asked to choose one of the alternative response options while still rehearsing the number. A final screen prompted participants to enter the memorized number. This sequence was repeated for each problem. Recollection errors were used as a manipulation check. Participants were also presented with 10 filler problems along with the experimental problems. These fillers were used in order to guarantee that participants could not anticipate the exact question corresponding to one of the types of experimental problems.

Table 1

Mean Proportion of Dominant Answers for Inclusion Problems, Nonstatistical Answers for Exclusion Problems, and Estimates of H and RB Across Instruction Conditions

Condition	Problem version		Estimate	
	Inclusion	Exclusion	H	RB
Intuitive	.69	.59	.70	.10
Rational	.80	.47	.76	.33

Note. For both conditions, $n = 19$. H = heuristic reasoning; RB = rule-based reasoning.

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[5] 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 .10. Thus, when predicting change (one-tailed tests), Ho will be rejected for α < .05; when predicting invariance (two-tailed tests), Ho will be rejected for α < .10.

Besides base-rate problems, conjunction problems, and ratio-bias effect problems, Experiment 2 included a new type of problem based on the law of large numbers (LLN), inspired by problems proposed by Nisbett et al. (1983; Fong et al., 1986). 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 nonstatistical processing based on representativeness). In the inclusion versions of these problems, both H and RB processes favored the same option.

Filler problems were identical to experimental problems except for the question and alternative response options. For instance, following a ratio-bias effect problem in which Mark has to draw a ticket from one of two bowls containing 1 out of 9 and 9 out of 91 "winner" tickets, participants were asked: How many "winner" tickets are contained in the first bowl?

(a) 1 ticket

(b) 5 tickets

Data analysis of Experiment 2 considered participants' responses to eight problems (four base-rates problems, one conjunction problem, two law of large numbers problems, and one ratio-bias effect problem).

Design. The design is a $2 \times 2 \times 2 \times 2$ factorial with cognitive load (high and low), problem versions (List 1 and List 2), and problem order (List A and List B) as the between-subjects variables and type of problem (inclusion and exclusion problems) as the within-subjects variable.

Results

Several separate one-way ANOVAs showed no order effects on the RB and the H estimates. Therefore this factor is not discussed further. However, significant version effects were obtained for both RB estimates, $F(1, 102) = 21.77$, $MSE = 0.08$, $p = .00$, and H estimates, $F(1, 102) = 4.24$, $MSE = 0.05$, $p = .05$. Nevertheless, the following analysis reports results collapsed across this variable because data analysis performed by version showed the same pattern of results and a difference in degree only. Inclusion and exclusion results as well as H and RB estimates are presented in Table 2.

The proportion of dominant answers (inclusion problems) was quite stable across cognitive load conditions. The decrease of nonstatistical answers from the high-load to the low-load condition for exclusion problems indicates that the secondary memory task interfered with participants' performance.

An ANOVA, with the two cognitive load conditions as a between-subjects variable, was performed on the RB and H estimates as repeated measures. The analysis revealed a reasoning mode main effect, indicating that H is greater than RB, $F(1,$

Table 2
Observed Mean Proportions of Dominant Answers for Inclusion Problems, Nonstatistical Answers for Exclusion Problems, and Estimates of H and RB Across Cognitive Load

	Problem version		Estimate	
Condition	Inclusion	Exclusion	H	RB
High load[a]	.79	.57	.78	.23
Low load[b]	.80	.46	.77	.35

Note. H = heuristic reasoning; RB = rule-based reasoning.
[a] $n = 51$.   [b] $n = 52$.

$101) = 368,81$, $MSE = 0.03$, $p = .00$, and an interaction between cognitive load conditions and reasoning modes, $F(1, 101) = 6.31$, $MSE = 0.03$, $p = .01$. This interaction reflects the differential impact of cognitive load on H and RB estimates. Increasing the difficulty of the competing memory task (changing from one- to seven-digit numbers) produced a reduction in RB, $t(101) = 2.06$, $SD = 0.30$, $p = .02$ (one-tailed planned comparisons), whereas it left H largely unchanged, $t(101) < 1$, $SD = 0.23$ (two-tailed planned comparisons).

Participants who made many errors in the memory task for seven-digit numbers may not have been engaged in the cognitive load memory task. Hence, the statistical analysis was redone, eliminating participants who made more than three errors on the memory task. The pattern of results was basically unchanged, showing once more an interaction between cognitive load conditions and reasoning modes, $F(1, 77) = 4.74$, $MSE = 0.03$, $p = .04$. Planned comparisons also revealed a significant reduction of RB, $t(77) = 1.99$, $SD = 0.28$, $p = .02$ (one-tailed), and no significant change for H, $t(77) < 1$, $SD = 0.25$ (two-tailed).

Discussion

Cognitive load was manipulated through the introduction of a secondary memory task, which was meant to interfere with the primary judgment task. Cognitive load, as expected, had a differential effect on RB and on H by affecting the former but not the latter. The dissociation between H and RB again supports the operation of both processes for these judgments and supports the assumption that H is an efficient and effortlessly activated process, whereas RB is a controlled and resource consuming cognitive activity.

Experiment 3

The process dissociations reported so far resulted from the use of variables that are traditionally considered to affect controlled processes (intentional and resource consuming) such as RB and to have little impact on automatic processes (autonomous and efficient) such as H. Experiment 3 involves a manipulation known to affect H.

Dual-process models of judgment under uncertainty assume that H is often based on associative principles of similarity and temporal structure, whereas RB involves the cognitive manipulation of symbolic rules and is not expected to be affected by manipulations involving the priming of associative principles (Epstein, 1994; Epstein, Donovan, & Denes-Raj, 1999; Sloman, 1996). On the basis of this assumption, Experiment 3 used heuristic priming problems that, besides sharing the same statistical principle as the target problem, were very similar to target problems in terms of their superficial structure (subject matter and story outline) within each problem's type. The combination of the priming of heuristic use plus the similarity in superficial structure of the priming and target problems should increase the activation and the use of the H process. Consequently, estimates of H should increase in the priming condition. Furthermore, given that RB is expected to be largely insensitive to the problems' superficial structure, it should be unaffected by heuristic priming.

Method

Participants. The participants were 95 students (26 men and 69 women) at Indiana University who participated to partially fulfill a requirement of their introductory psychology course.

Procedure and material. The material included target problems, heuristic priming problems (all with an exclusion problem format), and neutral problems. Because H is expected to be induced for later problems that have

similar superficial structures to the initial heuristic priming problems, new target problems with similar superficial structure to the initial heuristic priming problems were developed. There are two main differences between priming problems and target problems. One is that priming problems do not have inclusion versions; they are all exclusion problems. The other is that the target description information of priming problems is so diagnostic that, even in the face of opposing statistical information, the nonstatistical response option is more appropriate than the statistical response option. In this case, the nonstatistical response is actually the more correct response. In order to prime heuristic use, we needed to make the H-based information so strong that it would dominate the judgment. 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, breast-fed the children, and a DNA test shows the presence of XX chromosomes. Is the person a woman or a man? Despite the high base rate of men, the information is even more diagnostic, and H-based judgments yield the better answer. Our target problems, however, maintain the same form as in the other experiments. Thus, we continue to use the terms statistical and nonstatistical for RB-based versus H-based answers, respectively, for target exclusion problems.

Neutral problems neither involve inductive reasoning nor 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 subsequent question was as follows: Where would you prefer to live?

(a) In a big city like New York.

(b) In a small city like Bloomington.[6]

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 were very similar to the priming problems in terms of their superficial features. The control condition was equivalent to the priming condition, except that priming problems were replaced by neutral problems. Participants responded to a set of 8 target problems following 24 priming problems (or 24 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 $2 \times 2 \times 2 \times 2$ factorial with priming manipulation (heuristic priming and control condition), problem versions (List 1 and List 2), and problem order (List A and List B) as the between-subjects variables and type of problem (inclusion and exclusion problems) as the within-subjects variable.

Results

Several separate one-way ANOVAs showed neither version nor order effects on the RB and H estimates. Therefore these factors are not discussed further. Inclusion and exclusion results as well as H and RB estimates are presented in Table 3.

In the heuristic priming condition, the proportion of both dominant answers for inclusion problems and nonstatistical answers for exclusion problems increased. An ANOVA was performed, with heuristic priming as a between-subjects variable and RB and H estimates as repeated measures. The analysis revealed a reasoning mode main effect, indicating that H is greater than RB, $F(1, 75) = 163,69$, $MSE = 0.05$, $p = .00$, and a Heuristic Priming $\times$ Reasoning Mode interaction, $F(1, 75) = 3.87$, $MSE = 0.05$, $p = .05$. As predicted, planned comparisons indicated that priming H pro-

Table 3

Observed Mean Proportions of Dominant Answers for Inclusion Problems, Nonstatistical Answers for Exclusion Problems, and Estimates of H and RB Across Conditions

Condition	Problem version		Estimate	
	Inclusion	Exclusion	H	RB
Control[a]	.74	.42	.70	.32
Priming[b]	.83	.53	.83	.30

Note. H = heuristic reasoning; RB = rule-based reasoning.
[a] $n = 37$.　[b] $n = 40$.

duced an increase in H, $t(75) = 2.278$, $SD = 0.24$, $p = .01$, (one-tailed), whereas it left RB largely unchanged, $t(75) < 1$, $SD = 0.18$ (two-tailed).

For participants who made wrong answers to priming problems, heuristic processing was likely not primed. To check for this possibility, we redid the above analyses including only participants with three or fewer errors to priming problems. The resulting Heuristic Priming $\times$ Reasoning Mode interaction, $F(1, 62) = 4.12$, $MSE = 0.05$, $p = .05$, reflects the same pattern of results as the analysis conducted with all participants. As predicted, planned comparisons revealed an increase in H from the control to the priming condition, $t(62) = 1.90$, $SD = 0.25$, $p = .03$ (one-tailed), as well as an invariance of RB estimates across control and priming conditions, $t(62) < 1$, $SD = 0.38$ (two-tailed).

Discussion

Experiment 3 was designed to test the impact of heuristic priming on RB and H processes. 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, the priming manipulation of Experiment 3 increased H's activation level enough so as to augment heuristic-based responses to subsequent target problems that had weak individuating information. Similarly, priming problems may have also promoted output convergence to the expected heuristics-based response option (i.e., nonstatistical responses to exclusion problems and dominant responses to inclusion problems) by reducing the frequency of idiosyncratic answers. On the other hand, 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. These results provide supporting evidence for dual-process accounts for the judgments involved in the problems used here that postulate the existence of two qualitatively different modes of reasoning, one based on the symbolic operation of localized representations of inductive

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[6] See Appendix B.

rules (RB), and the other based on the parallel operation of associative principles of similarity and temporal structure (H; e.g., Sloman, 1996).

Experiment 4

Research on formal operations has shown that the mere induction of formal thought (as opposed to concrete thought) generally increases the subsequent use of abstract reasoning (LaRue & Olejnik, 1980). Experiment 4 primed participants with formal problems (derived from Graduate Record Exam [GRE] problems) before they responded to the same kind of target problems used in Experiments 1, 2, and 3. Because RB is usually described as abstract inductive reasoning, it should be responsive to formal pretraining. However, the formal problems were completely different from the target problems in terms of their superficial structure (i.e., the subject matter and the story outline) as well as in terms of their deep structure (i.e., the reasoning rules involved). Hence, a reasoning mode based on principles of similarity and temporal structure, such as H involves, cannot be affected by such pretraining. Thus, it is predicted that formal training will promote subsequent RB, whereas it will leave H largely unchanged.

Method

Participants. The participants were 107 students (52 men and 55 women) at Indiana University who participated to partially fulfill a requirement of their introductory psychology course.

Procedure and material. The material included target problems, formal problems, and neutral problems. The formal problems were based on actual GRE problems. Finding the correct answer to these problems implies different sorts of formal reasoning. Specifically, the problems involve conditional reasoning (e.g., to find out which of two response options is in agreement with a set of conditional rules), abstract reasoning (e.g., to choose between two interpretations of proverbs, an abstract and a concrete one), and semantic reasoning (e.g., to choose between pairs of words that best express a relationship that is a better analogy to a previously presented pair of words). Neutral problems were equivalent to formal problems except that the reasoning questions were replaced by trivial questions concerning participants' interests, opinions, or preferences related to mundane aspects of their lives.[7] Target problems were equivalent to the experimental problems of Experiments 1 and 2 and thus did not share a similar superficial structure with the formal problems.

Participants were randomly assigned to the formal training condition or to the neutral problem control condition. Problems were organized in four blocks, one for each type of target problem [base-rate problems, conjunction problems, problems based on the law of large numbers and ratio-bias effect problems). Within each block, participants in the formal condition responded to 8 formal problems followed by two target problems (one inclusion problem and one exclusion problem). Participants in the neutral condition responded to 8 neutral problems followed by the same two target problems. Thus, the control condition was the same as the training condition, except that priming problems were replaced by neutral problems. Thus, in total, participants responded to a set of 8 target problems plus either 32 initial priming problems or 32 initial neutral problems. Data analysis of Experiment 4 considered participants' responses to 6 target problems (2 base-rate problems, 2 LLN problems, and 2 ratio-bias effect problems).

Design. The design is a $2 \times 2 \times 2 \times 2$ factorial with priming manipulation (formal reasoning and control conditions), problem version (List 1 and List 2), and problem order (List A and List B) as the between-subjects variables and type of problem (inclusion and exclusion problems) as the within-subjects variable.

Results

Several separate one-way ANOVAs revealed no version or order effects on the RB and H estimates, except for a significant version effect for the H estimate, $F(1, 68) = 4.29$, $MSE = 0.06$, $p = .04$. The statistical analysis that follows reports results collapsed across this variable because data analysis comparing Version 1 with Version 2 showed the same pattern of results and a difference in degree only. Inclusion and exclusion results as well as H and RB estimates are presented in Table 4.

Formal training affected responses to exclusion problems in the expected direction, leading to an increase in statistical answers. However, this training had virtually no effect on responses to inclusion problems. An ANOVA was performed with formal training (vs. control) as a between-subjects variable and the RB and H estimates as repeated measures. The analysis revealed a reasoning mode main effect, indicating that H is greater than RB, $F(1, 68) = 283,48$, $MSE = 0.02$, $p = .00$, and a formal Training $\times$ Reasoning Mode interaction, $F(1, 68) = 4.07$, $MSE = 0.02$, $p = .05$. As predicted, planned comparisons showed that formal training promoted RB, although this promotion did not reach conventional levels of statistical significance, $t(68) = 1.43$, $SD = 0.30$, $p = .08$ (one-tailed), and it left H unaltered, $t(68) < 1$, $SD = 0.25$ (two-tailed).

The above analysis was redone to include participants with four or fewer errors to the formal problems (this corresponds to an average of fewer than one error for each block of formal problems).[8] The pattern of results was the same as the analysis conducted with all participants, with a significant Formal Training $\times$ Reasoning Mode interaction, $F(1, 58) = 5.94$, $MSE = 0.02$, $p = .02$. Planned comparisons revealed an increase in RB from the control to the training condition (although it did not quite reach conventional levels of statistical significance), $t(58) = 1.49$, $SD = 0.30$, $p = .07$ (one-tailed), as well as an invariance of H estimates across control and priming conditions, $t(58) < 1$, $SD = 0.25$ (two-tailed).

Discussion

Experiment 4 directly tested a prediction stemming from related literature showing that priming formal thought is sufficient to induce subsequent abstract reasoning (LaRue & Olejnik, 1980). Given that RB is a form of rule-based symbolic reasoning, as proposed by different dual-process models of judgment under uncertainty (e.g., Stanovich & West, 2002), it was predicted and was found to be responsive to formal training that involves abstract reasoning. H, however, does not involve rule application or a complete formal description of concepts. Instead, it is based on automatic responses involving simplifying principles such as similarity or availability. Accordingly, it was insensitive to the priming effect of formal problems. Thus, results support the prediction that the priming of formal thought induces general, abstract rule application regardless of any specific operations attributable to the features of problems.

General Discussion

Judgment under uncertainty has recently been approached from the perspective of dual-process models (Griffin, Gonzalez, &

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[7] See Appendix C.

[8] Note that four or fewer errors in Experiment 4 and three or fewer errors in Experiment 3 correspond to the same criterion of 87.5% or more of correct answers for both cases.

Table 4

Mean Proportion of Dominant Answers for Inclusion Problems, Nonstatistical Answers for Exclusion Problems, and Estimates of H and RB Across Formal Training and Control Conditions

Condition	Problem version		Estimate	
	Inclusion	Exclusion	H	RB
Control[a]	.83	.50	.81	.33
Training[b]	.84	.40	.81	.44

Note. H = heuristic reasoning; RB = rule-based reasoning.
[a] $n = 31$.　[b] $n = 39$.

Varey, 2001; Kahneman & Frederick, 2002; Stanovich & West, 2000, 2002). 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), induced by situational as well as internal factors. 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 processing modes as they apply specifically to judgments under uncertainty has been mostly a matter of assumption, with surprisingly little direct empirical support. The intent of the work reported here is to change this state of affairs by providing direct evidence of the dual-process nature of judgment under uncertainty on the basis of the involvement of both H and RB as independent processes. Specifically, we used the PDP to assess both H and RB and to demonstrate theoretically derived process dissociations. These experiments convincingly show that variables traditionally associated with controlled processes affected RB but not H processes. Conversely, a variable already known to affect automatic processes affected H but left RB unchanged. Results across the four experiments strongly 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 such that an increase in one type of process does not indicate a decrease in the other type. In addition, the results demonstrate that simply assessing statistical or nonstatistical responses cannot reveal the level of rational or heuristic processing.

Experiment 1 manipulated participants' goals through instructions to answer a set of inferential problems in an intuitive way, or to answer these problems in a more reflective way. Instructions affected RB in the predicted direction, whereas they left H unchanged. The results of Experiment 1 thus indicate that RB is sensitive to goals to respond accurately, whereas H is insensitive to such goals or to incentives to respond accurately (e.g., Tversky & Kahneman, 1974).

Past research is consistent with our findings. Zukier and Pepitone (1984) found greater attention to base-rates when participants were instructed to think like scientists (as opposed to thinking like clinical psychologists). Ginossar and Trope (1987) found greater use of the sampling rule (in base-rate problems) to the extent that it was instrumental to reach previously defined goals. The present results suggest that these effects (i.e., decreasing judgmental errors [or biases] by role-playing, increasing the instrumental value of

goals or financial incentives) are independent of H and are exclusively due to an increase in RB.

In Experiment 2, we obtained H and RB estimates under low versus high cognitive load, testing the effect of a resource-demanding task on the two processing modes. As expected, an increase in cognitive load reduced RB processes but left H processes invariant, confirming the efficient operation of heuristic-based judgments.

Experiment 3 primed participants with inferential problems designed to facilitate H that shared the same superficial structure as the target problems and were presented sequentially prior to the target problems. Such heuristic priming significantly increased H processes, but it 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 more automatic processing principles underlying H.

As a type of abstract reasoning, RB should be responsive to formal training (e.g., LaRue & Olejnik, 1980). However, H is expected to be insensitive to formal training given its automatic nature. Experiment 4 used formal problems as primes for subsequent target problems. These priming problems were completely different from the target problems in terms of their superficial structure as well as their deep structure (i.e., no statistical rules were involved). As expected, H was not affected by these primes. However, rule-governed thinking involved in solving the priming problems led to an increase of RB.

Because different types of inferential problems were used (involving base-rates, the conjunction rule, the ratio-bias effect, and the LLN), it is important to provide some indication that the results were not due to responses to a specific type of problem in particular but were the outcome of all types of problems. Unfortunately, for most cases there were not enough problems of each type to compute reliable process estimates. Instead, data from each experiment were reanalyzed by problem (aggregating across participants). H and RB estimates were then computed for all combinations of two types of problems at a time. Mean results for H and RB obtained in this manner show exactly the same predicted result pattern for all problem types within each of the four experiments.

Findings of Invariance and the Assumption of Independence

As already noted, demonstrating situations in which H and RB contribute independently to judgments under uncertainty is a prerequisite for avoiding a process-pure assumption and does not reflect any theoretical claim about the possible modal interaction between these two processes. The independent dual-process model assumed by the PDP appears to be justified within the present paradigm given that the correlation between H and RB estimates across all studies was near zero ($r = -.08$, *ns*),[9] which strongly suggests functional independence.

Automatic and Controlled Influences in Social Judgments

Much social cognition research has been concerned with the interaction between cognitive control and automatic bias in social

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[9] Before computing this mean, correlations of RB and H were first computed for each experiment and transformed into Fisher's significance test scores.

judgments. The bias component of social judgment has gained importance over the years. At first, it was viewed as response error that should be corrected in order to better estimate "true" social judgments (e.g., Cohen, 1981; Hartwick, 1979); next, it came to be recognized as an important side-effect of the normal use of cognitive schemas (e.g., W. Brewer & Nakamura, 1984; Rumelhart, 1984); and most recently, the bias component is considered the implicit process constituent of dual-process approaches (Chaiken & Trope, 1999). It is important to note that although work in several areas of social cognition assumes the operation of both heuristic and systematic processes, until recently there was little in the way of independent assessment of these two processes as aspects of social cognition. Thus, regardless of the way in which automatic and controlled influences on judgment are interpreted, recent methodological tools that allow for the measurement of both influences within the same task have contributed greatly to our understanding of the two influences. Among these are signal detection theory (Correl, Park, Judd, & Wittenbrink, 2002; Green & Swets, 1967), the PDP, and other polynomial models (see Batchelder & Riefer, 1999) such as the guessing-corrected, multinomial process-dissociation analysis developed by Buchner and Wippich (1996); Klauer and Wegener's (1998) model of multiple memory discriminability and bias parameters; and the recently proposed Quad model (Conrey, Sherman, Gawronski, Hugenberg, & Groom, 2005).

The PDP in particular has been applied in different domains with implications for several areas of social cognition such as perception (Debner, & Jacoby, 1994), habit and recollection (Hay & Jacoby, 1996), proactive interference (Jacoby, Debner, & Hay, 2001), explicit versus implicit memory in judgments of fame (Jacoby et al. 1989; Jennings & Jacoby, 1993), and most recently the controlled and automatic influences of prejudice and social stereotypes (Lambert et al., 2003; Payne, 2001; Sherman, Groom, Ehrenberg, & Klauer, 2003).

Automaticity and Heuristic Reasoning

H was regarded as an instance of Sloman's (1996) associative system. Furthermore, this reasoning mode was considered to share at least some of the key aspects of automatic processes (Bargh, 1994). In fact, H appears to involve few cognitive resources and to operate with little awareness or process control. H also seems to lack some of the defining features of control, namely the ability to monitor information processing so as to flexibly vary it in response to feedback (Wegner & Bargh, 1998).

In the case of Jacoby's (1991) process dissociation procedure, automatic processes are typically viewed as a bias in facilitating certain responses that becomes apparent when controlled processes fail. The exact nature of this bias varies. In Jacoby's model, the bias is familiarity bias or processing fluency bias (Jacoby, Toth, & Yonelinas, 1993), whereas in our case it is heuristic processing bias. Moreover, 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 terms *heuristics* or *heuristic reasoning* that do not accommodate this conception of automaticity refer to reasoning forms that could not be separated from (controlled) RB by using the PDP and as such are beyond the scope of the present definition of H.[10] Other dual-process approaches to reasoning adopt a conception of automaticity that is similar to our own (Evans & Over, 1996; Kahneman & Frederick, 2002; Stanovich & West, 2000).

The Perfect Performance Problem

The PDP assumes independence between automatic (H) and controlled (RB) processes and uses the proportion of nonstatistical answers in the exclusion test to estimate the strength of H. Thus, if no nonstatistical answers are given in the exclusion test (exclusion = 0), the heuristic component cannot be estimated. The relative number of cases discarded due to exclusion = 0 was very low for Experiment 1 (2.5%) and Experiment 2 (8.0%), moderate for Experiment 3 (18.9%), and relatively high for Experiment 4 (34.6%). Exclusion of these data has no effect on the process dissociations here reported (based on the PDP estimates) as long as the H and RB processes are independent. However, if the two processes are positively correlated, H will be underestimated by the PDP, and this underestimation will be higher for higher levels of RB. Why? Because, if a positive correlation between H and RB exists, then H processes will no longer be equivalent under higher and lower levels of RB. In fact, when a positive correlation exists, H will be higher when RB is higher and lower when RB is lower, and as we are estimating H from the proportion of nonstatistical answers to exclusion problems (i.e., when RB is lower), we will necessarily underestimate H. Under these circumstances, eliminating participants with perfect performances would facilitate the emergence of artifactual dissociations because we are eliminating the participants for whom RB is highest.

In any case, H and RB estimates calculated from data collapsed by participants and by problems (the grand means) are unaffected by exclusion = 0 and provide a way to test for the above possibility (Curran & Hintzman, 1995; Jacoby et al., 1993; Toth, Reingold, & Jacoby, 1994). Thus, we recomputed H and RB in this way and used the standard error of the proportion to derive 95% confidence intervals around the grand means. The pattern of results coincides with that of the original data analyses (although collapsing across participants and problems precludes the computation of statistical interactions). Multinomial modeling analyses that included participants with perfect performance (exclusion = 0) was also used and the fit of the model estimates was good, reproducing therefore the pattern of results we obtained in our original analyses. Regardless, exclusion performance = 0 should be avoided in future studies that test new hypotheses involving the interaction of the two processing modes, perhaps by increasing the number of target problems.

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[10] Because 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 nonstatistical 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. For instance, choosing the nonstatistical option based on deliberate and controlled reasoning would imply that fewer resources would produce fewer errors to exclusion problems, canceling the predicted decrease of RB as a function of cognitive load or even inverting this tendency.

Relationship to Other Dual-Process Approaches

The PDP approach differs in two significant ways from other dual-process approaches to understanding judgment and decision making. First, the PDP conceptualization of RB and H processes as two independent and parallel reasoning modes differs from models that conceive of them as mutually exclusive. For example, 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., M. B. Brewer, 1988; Fazio, 1990; Kahneman & Tversky, 1972, 1973; Petty & Cacioppo, 1981). Other models (e.g., Fiske, Lin, & Neuberg, 1999; Fiske & Neuberg, 1990) have argued that RB and H represent two ends of a continuum and that movement toward one end of the continuum (e.g., H or RB) necessarily coincides with diminished activity on the other end (e.g., RB or H). 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 (Epstein, 1991; Kahneman, 2003; Sloman, 1996; Smith & DeCoster, 2000; Strack & Deutsch, 2005). However, only the PDP approach also offers a means for independently assessing the joint contributions of these processes to performance on a single task (see the following paragraph).

The second significant difference between the PDP approach and other dual-process approaches concerns the means of estimating RB and H. Many dual-process approaches have relied on content dissociations to infer the extent to which a judgment reflects relatively heuristic or systematic processing. For example, the classical approach to understanding judgment under uncertainty is to associate the influence of one kind of information (e.g., base-rate information) with systematic processing (RB) and the influence of another kind of information (e.g., stereotypic target descriptions) with the use of heuristics (e.g., Kahneman & Tversky, 1972, 1973). Other dual-process approaches have attempted to estimate RB and H by administering two separate measures, one aimed at tapping an automatic process (reflecting H) and one aimed at tapping a controlled process (reflecting RB).

A significant drawback to content dissociations is that they incorporate a confound between content and process. Though it may be the case that some kinds of information (e.g., heuristic cues) are typically applied with more ease and with less intent than other kinds of information (e.g., base rates), it is not difficult to find or induce exceptions to this state of affairs (e.g., Krull & Dill, 1996; Kunda & Thagard, 1996; Trope & Alfieri, 1997). Administering separate measures confounds the processing style (H vs. RB) with the particular measurement task (e.g., IAT vs. questionnaire). This is a problem because the chosen tasks may differ in a number of ways beyond the extent to which they tap automatic versus controlled processes (e.g., Jacoby, 1991; Roediger, 1990; Sherman, 2006). From the PDP perspective, the application of any type of information always reflects a combination of heuristic and systematic processes, and these processes can be estimated simultaneously from a single response, independently of particular content (for a review, see Sherman, 2006). Indeed, the PDP was developed specifically to overcome task confounds in the implicit–explicit memory literature (e.g., Jacoby, 1991).

Thus, the PDP approach adopted for understanding judgment under uncertainty offers important theoretical and methodological advantages over other dual-process approaches. Theoretically, it avoids fragile assumptions of process purity and process exclusivity, embracing the view that all judgments recruit parallel and independent heuristic and systematic processes that interact to produce output. Methodologically, it offers a means for measuring the independent contributions of the two processes within a single task, thereby avoiding content and task confounds that threaten the validity of dual-process conclusions.

On the Relationship Between H and RB Processes

The C-first model. In the PDP model that we applied in our data analyses (Jacoby, 1991), the RB process constrains the influence of the H process. That is, the equations are such that the influence of H is observed only in cases in which RB does not provide a response. Note that designation of C-first is not meant to reflect temporal sequence. As Payne, Jacoby, and Lambert (2005) explained

> [T]he order depicted in this model refers to logical priority, not temporal ordering. The model is not sequential. We assume both processes begin at the same time and proceed simultaneously and independently. The priority of one process over the other means that the second process can drive the behavior only in the absence of the first. If both processes occur, then the first one dominates and determines the response. (p. 412)

Rather, this describes the mathematical relationship between the processes in producing judgments. Thus, the RB and H processes are thought to occur simultaneously. However, in determining a response on a trial of a given task, the influence of H is seen only in cases in which RB fails to provide a response. In this way, the RB process dominates or constrains the H process in this model. As such, this model may be called the *C-first* (control) model, and it has been applied to separate the automatic and controlled components of behavior in many areas of research, including perception (Debner & Jacoby, 1994), habit and recollection (Hay & Jacoby, 1996), proactive interference (Jacoby et al., 2001), judgments of fame (Jacoby et al., 1989; Jennings & Jacoby, 1993), and stereotyping (Lambert et al., 2003; Payne, 2001; Sherman et al., 2003).

The A-first model. However, it is clear that automatic and controlled processes do not always interact in this C-first fashion. Instead, in some cases, it is 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; Stroop, 1935), the automatic habit to read the word captures attention and interferes with the more controlled process of naming the color of the ink.

Lindsay and Jacoby (1994) proposed a variation on the original C-first PDP model to account for such situations. This may be referred to as the *A-first* model. The logic of the A-first model is identical to that of the C-first model (Jacoby, 1991), except that the roles of A and C have been reversed, resulting in slightly different equations in solving for A and C. In the A-first model, A and C are solved by comparing correct responses on inclusion (the word *blue* in blue ink) trials to correct responses on exclusion (the word *blue* in red ink) trials. The probability of a correct response on inclusion trials is $A + C (1 - A)$; the same as for the C-first model). The probability of a correct response on exclusion trials is $C (1 - A)$—when control drives the response in the absence of the auto-

matic process. A is solved by subtracting the probability of correct responses on exclusion trials from the probability of correct responses on inclusion trials. C then equals the probability of correct responses on exclusion trials divided by $(1 - A)$.

Choosing a model. In applying the PDP approach, it is not always perfectly clear a priori whether the C-first or the A-first model is more appropriate. As a consequence, the question of which model to apply is often treated as an empirical question (e.g., Batchelder & Riefer, 1999). For example, in Payne's (2001) research on automatic and controlled components of stereotyping, participants are required to identify objects as either guns or tools in the presence of Black and White faces. Conceivably, one could view this as a case in which the automatic influence of stereotypes activated by the faces would always influence responses, unless the stereotype either was not activated or it was somehow overcome. However, because the C-first model has consistently provided a better account of results with this task than the A-first model (e.g., Payne et al., 2005), it is the C-first analyses that are reported in this research. It is important to note that, although the choice of which model to apply may be an empirical one, that choice does constrain subsequent interpretation of the data. For example, Payne and his colleagues were careful to interpret their A parameter as a stereotypic bias that influences judgments only when controlled efforts to identify the object fail. Similarly, the controlled process is identified as a process that attempts to correctly identify the object (gun or tool) rather than a process that attempts to correct for the influence of automatic stereotypes after they have already been activated (that would be according to Payne et al., 2005, an A-first depiction of control).

One way to empirically distinguish between the models is to run separate analyses on the A and C estimates derived from the two models and to observe whether one model provides a more theoretically parsimonious accounting of the data than does the other. In addition to the C-first model analyses reported in the Results sections, we also conducted analyses for each study on the basis of the A-first equations. In Experiment 1, although the results showed the same basic pattern as the C-first analysis, the A-first model did not demonstrate clear support for the theoretically derived hypotheses. The key interaction between instruction (rational vs. intuitive) and processing mode (H vs. RB) was not reliable ($F < 1$). Planned comparisons demonstrated marginally greater RB in the rational than in the intuitive condition, $t(35) = 1.44$, $p < .09$, and no differences in H between the two conditions ($t < 1$).

Contrary to our hypothesis, and contrary to the C-first analysis, the A-first analysis of Experiment 2 showed no effect of the load manipulation on RB. There was no significant interaction between processing load (high vs. low) and processing mode (H vs. RB; $F < 1$). Neither H nor RB was affected by the load manipulation (both ts < 1, planned comparisons).

The A-first analysis of Experiment 3 demonstrated no significant interaction between priming (heuristic priming vs. control) and processing mode (H vs. RB), $F(1, 83) = 1.35$, $p < .25$. Instead both estimates increased as a function of the priming. The increase in H, $t(83) = 2.93$, $p < .05$, is expected and consistent with the C-first model, but the increase in RB, $t(83) = 2.49$, $p < .05$, is not.

Finally, the A-first analysis of Experiment 4 demonstrated a significant interaction between training (formal training vs. control) and processing mode (H vs. RB), $F(1, 103) = 5.10$, $p < .05$. However, planned comparisons showed that formal training marginally reduced H, $t(103) = 1.67$, $p < .10$, but had no effect on RB

($t < 1$). Neither finding was predicted or consistent with results from the C-first model.

In summary, the C-first model provides a more theoretically parsimonious account of the data across the four experiments than does the A-first model. In the C-first analyses, the manipulations influenced the appropriate processing modes in theoretically consistent ways. In contrast, in the A-first analyses, the manipulations did not influence the processing modes in a predictable fashion. Given the wealth of past process dissociation research validating the automatic and controlled nature of H and RB (A and C), this suggests that the C-first model provides a better account of the current data than does the A-first model. This does not necessarily imply that all judgment and decision making proceeds in a C-first rather than A-first fashion. Further research will be needed to delineate the particular types of judgments and contexts associated with the two different relationships between automatic and controlled processing.

Another way to empirically distinguish between the models is to compare their ability to account for the data through the use of maximum likelihood statistics and multinomial modeling. We applied such techniques to both C-first and A-first models of each experiment. Results showed that both models provided adequate fits of the data for Experiments 1, 2 and 4, but only the C-first model provided an adequate fit of data for Experiment 3. Thus, although this modeling does not clearly distinguish whether the C-first or A-first model is most appropriate for most of the current judgment tasks, the C-first model is the only one that accounts for the entire result patterns. Further information on the modeling is available from the authors.

Conclusion

One of the most important contributions of the heuristics and biases research programs was to bring the study of judgments under uncertainty into the realm of cognitive psychology and social cognition. However, apart from a few exceptions (see Weber, Goldstein, & Barlas, 1995; Weber, Goldstein, & Busemeyer, 1991), the promised integration has not lived up to expectations. In fact, most models of inductive judgment do little to explicitly combine considerations of memory processes, representation of information, categorization, and so forth, with other stages of the decision process. Now, as before, there is a need to articulate research in inductive judgment with the general conceptual framework of social cognitive research.

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. The resulting dual-process approach makes use of several psychological distinctions such as symbolic, localized representations usually coupled with rule-governed processing versus distributed representations of information generally attached to associative processing (Smith & DeCoster, 1999). In essence, we aimed to explore 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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(*Appendixes follow*)

Appendix A

Examples of the Problems Used[A1]

Base-Rates Problem

One hundred undergraduate students applied for a part-time job. Of the applicants, 15 (85) were humanities students, and 85 (15) were science students. Mike was one of the 100 students who applied for the job. His name was randomly chosen by computer to participate in the first day of interviews. Mike is 23 years old, he likes to travel, and he was quite a good student in high school. His preferred subjects were English poetry, modern art, and sports.

Which of the following is more likely?
(a) Mike is one of the humanities students.
(b) Mike is one of the science students.

Conjunction Problem

A company that makes beauty products is about to launch a new product line. The marketing department wanted to begin with the promotion of this new line as quickly as possible. To do this they can either deliver all the promotional work to a large publicity agency, or they can divide the promotional work between two smaller publicity agencies. The large agency has a record of meeting deadlines of 60% (90%). One of the smaller agencies has a record of meeting deadlines of 80%, and the other has a record of meeting deadlines of 70%. The marketing department can begin the promotion only when all the promotional work is ready to be used.

Which of the following is more likely?
(a) The best possibility of starting the promotion sooner would be to deliver all the promotional work to the larger publicity agency.
(b) The best possibility of starting the promotion sooner would be to divide the promotional work between the two smaller agencies.

Ratio-Bias Effect Problem

Elaine was on a TV show where she had to choose an envelope from one of two sets of envelopes. In the first set, there were 100 envelopes, 21 (19) of which contained a prize ticket of $5,000. In the second set, there were 10 envelopes, 2 of which contained a prize ticket of the $5,000.

If you were Elaine, what would you do?
(a) I would choose an envelope from the first set of envelopes.
(b) I would choose an envelope from the second set of envelopes.

Law of Large Numbers Problem

In their graduation year, students in theatre are chosen to act in a play to be presented at the end of the year. For this year's play, the professors have to decide between two students (Suzanne and Amy) for the main role in the play. Suzanne played brilliantly in several main roles during the 3 years of the theatre course, but (and) her audition for the present main role was mediocre (also brilliant). Amy's performance in several main roles during the course was mediocre but (and) her audition to the present main role was brilliant (also mediocre).

What do you think is more likely?
(a) Amy has a better possibility of being selected.
(b) Suzanne has a better possibility of being selected.

Filler Problem

Sylvia is a 35-year-old woman. She is intelligent, pretty, an excellent debater, and she is very captivating. Since she was a girl, Sylvia was interested in journalism. After finishing high school, Sylvia majored in Social Communication and Journalism with excellent grades. Given that she was one of the best students in her major, she rapidly initiated a very successful professional career.

Since she was a girl, Sylvia was interested in what?
(a) science fiction
(b) journalism

Appendix B

Example of a Heuristic Priming Problem, a Neutral Problem, and a Target Problem Used in Experiment 3 (for Base-Rates Problems)[B1]

Priming Problem

One hundred men from the U.S. Army Special Forces were selected for a dangerous secret mission in South America. Ten of these men are officers, and 90 are privates. Bob is a veteran from the Vietnam War. He is often called for special missions, and he is used to commanding men under extremely difficult situations. Last year he was promoted and was decorated by the U.S. president for his accomplishments in the army and for his exceptional qualities of leadership.

Which of the following is more likely?

(a) Bob is one of the 10 officers in special forces selected for the mission.
(b) Bob is one of the 90 privates in the special forces selected for the mission.

[A1] Numbers in parentheses were used in the inclusion versions of the problems.

[B1] Numbers in parentheses were used in the inclusion versions of the problems.

Neutral Problem

The first time Chad went to New York he was very impressed with the city: the huge buildings, the nonstop activity, everybody always rushing, et cetera. Chad spent 2 weeks there and he loved it. However he also realized that he would not like to live in such a big city. There was too much confusion for him.

Where would you prefer to live?

(a) In a big city like New York.

(b) In a smaller city like Bloomington.

Target Problem

In the year 2467, after 50 years of war against the Cyclons (an alien species), the human race is about to be defeated. One hundred men from the U. N. Army Special Forces were selected for a dangerous secret mission in a last war effort. Twenty (80) of these men are majors, and 80 (20) are sergeants. Amos is a veteran from several battles against the Cyclons. He is often called for special missions, and he is used to commanding men under extremely difficult situations. Last year he was promoted and was decorated by the U. N. president for his accomplishments in the army and for his exceptional qualities of leadership.

Which of the following is more likely?

(a) Amos is one of the 20 (80) majors in special forces selected for the mission.

(b) Amos is one of the 80 (20) sergeants in the special forces selected for the mission

Appendix C

Examples of Graduate Record Exam Problems Used in Experiment 4

Three-person work crews are to be chosen from among two groups totaling seven people. Group I consists of A, B, C, and D. Group II consists of E, F, and G. Each group must have at least one representative in any possible work crew. C refuses to work unless E works. G will not work if A works.

Which of the following crew may not be assembled?

(a) A, C, E

(b) A, F, G

Building B is taller than Building C; Building A is taller than Building B.

Which is the shorter Building?

(a) Building B

(b) Building A

Which of the following pairs of words expresses a relationship that is a best analogy for the pair RACE–FATIGUE?

(a) TRACK–ATHLETE

(b) FAST–HUNGER

What is the best interpretation of the following proverb, "out of the pot, into the fire"?

(a) Sometimes people escape from a bad situation just to get into a worse one.

(b) If you put too much food in a cooking pot, food will spill out of the pot and fall right into the fire.

Which of the following pairs of words expresses a relationship that is the best analogy for the pair BIRTHMARK–CONGENITAL?

(a) BEAUTY SPOT–FACIAL

(b) BALDNESS–HEREDITARY

Example of a Neutral Problem

Three-person work crews are to be chosen from among two groups totaling seven people. Group I consists of A, B, C, and D. Group II consists of E, F, and G.

With which of the following do you agree more?

(a) Each group must have at least one representative in any possible work crew.

(b) It is better to form work crews with workers coming from the same group.