Motivating Base-Rate Sensitivity (Sometimes): Testing Predictions of the RCCL Framework

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Abstract

In choice situations, people are usually (but not always) sensitive to the base-rates of success of the options, and this base-rate sensitivity usually (but not always) goes up when motivation levels are increased. The RCCL framework, which emphasizes what information is represented by the individual and what strategies are used, provides an explanatory framework for these types of effects. In particular, RCCL predicts that manipulations of motivation levels should produce changes in the strategies being used, which will not produce a change in base-rate sensitivity for dimensions not represented in the strategies. This paper reports an empirical test of these predictions; changes in strategy use and a lack of change in base-rate sensitivity are found, as predicted by RCCL.

Introduction

In making optimal choices in an uncertain world, a problem-solver must pay attention to the base-rates of success of each of the possible choices: the past success rates are usually good indicators of future success rates. For example, travel routes that were generally congested in the past are likely to be congested in the future. While one often finds base-rate insensitivity when base-rates are presented verbally in textual problems (e.g., Ginossar & Trope, 1987; Tversky & Kahneman, 1982), one usually finds extremely good base-rate sensitivity in experiential paradigms (e.g., Estes, Campbell, Hatsopoulos, & Hurwitz, 1989; Maddox, 1995). That is, when problem-solvers experience many decisions during problem solving, they are typically very sensitive to the base-rates of success that they have experienced. However, there are a few well-documented exceptions to this general trend of good base-rate sensitivity (Goodie & Fantino, 1995; Goodie & Fantino, 1996; Medin & Edelson, 1988).

A challenge for cognitive science is to come up with models that explain why and to what degree one observes base-rate sensitivity (or base-rate neglect). Recently Lovett and Schunn (1999) proposed RCCL (pronounced "ReCyCLe") as a framework for providing such an explanation.

RCCL specifies how task representations can influence choice in experiential base-rate situations. The four main stages of processing in RCCL are: (i) Represent the task, (ii) Construct a set of action strategies consistent with that task representation, (iii) Choose among those strategies according to their success rates, and (iv) Learn new success rates for the strategies based on experience. The primary theme underlying RCCL is that a task representation constrains the set of strategies an individual will use for taking actions in the task environment. Making choices according to the learned success rates of a certain set of strategies enables RCCL to produce base-rate sensitivity or base-rate neglect in direct-experience situations; sensitivity arises only when the constructed strategies include stimulus features that are important to success in the task. The RCCL framework also includes re-cycling through the above processes when the current representation and strategies lead to low success rates. This implies that an individual's task representation and strategy set need not be static but rather can develop with experience.

At this level of description, the components of RCCL may seem intuitive to the point of being obvious: how else could it be done? However, the central contribution of RCCL may be to forefront processes that are highly likely to be going on yet have been ignored in previous accounts of human choice processes. Moreover, there are accounts of choice processes that do not invoke (and perhaps even deny) the role of mental representations (e.g., Goodie & Fantino, 1995; Goodie & Fantino, in press).

Lovett and Schunn (Lovett & Schunn, 1999) described two experiments that provided empirical support for the RCCL framework. In one experiment they showed that people prefer representations and strategies that make use of information predictive of successful problem solutions. In the second experiment, they demonstrated that one could change the superficial characteristics of the task environment such that participants would prefer one representation or another, and that this manipulation determined what base-rates participants would learn.

The current paper seeks to further test RCCL specifically, and strategy-based accounts of choice processes more generally (e.g., ACT-R). The insight is to examine the effects of performance motivation on base-rate sensitivity in a problem-solving context.

To tease apart strategy and non-strategy-based accounts of choice processes, one needs to distinguish between simple and complex choice situations. In a simple choice situation there is a direct, one-to-one mapping between the person's strategies and external alternatives. That is, one can adequately describe the person's strategies in terms of simple external choices. For example, when presented with a left and right button to press, the person represents the choice strategies as Select-Right and Select-Left. By contrast, in a complex choice situation, there is not a simple mapping between strategies and external alternatives. That is, a given strategy might map onto different external alternatives on different trials; two different strategies may map onto the same external alternative on the given trial.

In very simple choice situations, strategy-based and non-strategy-based accounts make very similar predictions about the effects of motivation on base-rate sensitivity. The greater the value of a success, the more participants (human or otherwise) will prefer the more successful choice (see Anderson, Lebiere, & Lovett, 1998). In other words, greater motivation levels should produce higher base-rate sensitivity.

In complex problem-solving situations, however, RCCL makes two novel predictions regarding the effects of motivation. First, RCCL predicts shifts in strategy choice as a function of motivation changes when the strategies vary in terms of effort and success. That is, it is the selection among strategies (rather than externally defined alternatives) that is directly influenced by motivation. This prediction is easily formalized using various forms of expected utility theory (e.g., see Anderson et al., 1998). However, intuitively this prediction can be understood as people becoming more willing to put out the extra effort associated with a more effortful but more successful strategy when they are more motivated to succeed.

RCCL's second prediction is that this change in strategies may produce increases or decreases in base-rate sensitivity depending on whether the new or old strategies represent the external alternative feature whose base-rate is being manipulated. As an abstract example (the next section presents a concrete example), suppose there is a strategy S1 that does represent an external feature F1 (i.e., S1 makes direct use of feature F1 to make a choice) and a strategy S2 that does not represent external feature F1 (i.e., S2 makes choices without making use of feature F1). Then, when people use strategy S1, they will be sensitive to the base-rates with which F1 predicts success, whereas when they use strategy S2, they will not be sensitive to the base-rates with which F1 predicts success. Thus, if increasing motivation leads people to move from S1 to S2, then base-rate sensitivity to F1 will go down. By contrast, if increasing motivation leads people to move from S2 to S1, then base-rate sensitivity to F1 will go up. In general, for situations in which increases in motivation level cause a person to shift to a strategy that does not represent the relevant base-rate, then RCCL predicts decreases in base-rate sensitivity with increases in motivation level.

By contrast, non-strategy-based accounts would always predict an increase in base-rate sensitivity with increasing performance motivation. As the value of currently picking the best option increases, one should find better base-rate sensitivity (or even over-matching). Intuitively, the more incentive one has to do well, the more one pays attention to cues (e.g., base-rates) that will predict accurate choices.

The role of performance motivation in base-rate sensitivity and strategy adaptivity is also an important question for other reasons. Recent research (Schunn & Reder, 1998) has shown that there are individual differences in the degree to which people adapt their strategies to shifting base-rates of success, and that these base-rate sensitivity individual differences are correlated with individual differences in inductive reasoning skill. A remaining question, however, is whether these individual differences in base-rate sensitivity can also be partially explained by motivational differences (i.e., are the more base-rate sensitive participants simply the more motivated ones). The current research will show the degree to which base-rate sensitivity is influenced by motivation levels and thus whether there is a potential confound in the individual differences research in this area.

Methods

Participants

Ninety-two George Mason University undergraduates participated for course credit and were randomly assigned to one of two conditions. Nine participants encountered technical difficulties with the computer setup, and their data is not included in the analyses.

Building Sticks Task

In the building sticks task, participants are presented with 3 different-sized building sticks which they must choose among to create a given goal stick. To achieve the goal stick, participants add or subtract any combination of the buildings sticks provided.

For a given BST problem, using one of two approaches will result in the goal stick (Note, here I use the term "approach" to refer to an externally-defined alternative in contrast to a true strategy). Using the undershoot approach, participants start with a stick shorter than the goal stick and add to it to achieve the desired stick length. In the overshoot approach, participants pick a stick longer than the goal stick and subtract from it until the goal stick is created. Each problem is designed to be solved using one of the approaches, but not both.

For example, if the goal stick provided is 8 units in length and the 3 sticks A, B, and C, are 15, 6, 7, respectively, using the overshoot approach will solve this problem. To achieve the goal stick, participants start with stick A and subtract stick C (15 – 7 = 8) to reach the solution. Using the undershoot approach in this case would never result in the desired stick length because picking stick B and adding to it will not equal 8 (B + C = 6 + 7 = 13). Note that participants in the task are not given numerical lengths of the sticks. Instead, participants must estimate stick lengths and determine which sticks would lead to the goal stick before taking the appropriate steps. As a result, participants were forced to implicitly apply an approach (overshoot/undershoot) to solve each problem without knowing in advance whether it would work.

Participants were given 80 BST problems to solve. Participants worked through each problem until the goal stick was achieved. If a solution was not reached within 5 moves or less, participants were asked to reset the problem and start over again until the goal stick was reached. Each problem was designed to be solved by only one of the two approaches.

For the first 40 problems, the overshoot approach was biased to be more successful in solving the problems than the undershoot approach, with 70% and 30% success rates for each approach, respectively. For the second 80 problems, the success rates were reversed, with the undershoot approach biased to be more successful 70% of the time. This sequence was held constant across conditions. The degree to which participants adapted their approach choices to this base-rate manipulation is one of two primary dependent measures.

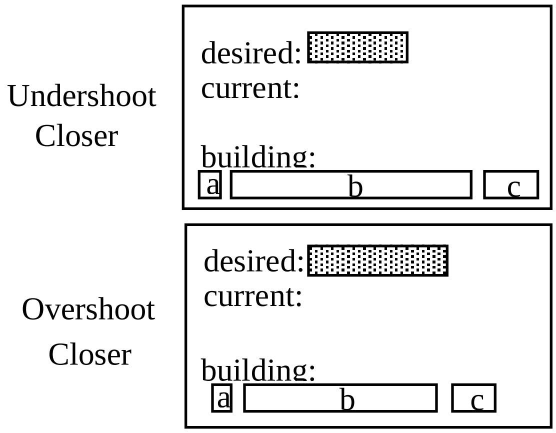

Figure 1. Examples of Undershoot looking (top) and Overshoot looking (bottom) BST problems.

In addition, each problem was designed with a feature pattern, called a relative length cue, which was predictive of the correct approach to use for a given goal stick. One of the 3 building sticks was designed to appear closer in length to the goal stick, suggesting a bias towards use of one approach over another. As shown in the top of Figure 1, stick C looks closest in length to the goal stick. Therefore, participants are more likely to start with stick C (initiating the undershoot approach) and adding segments until the desired stick length is reached. In contrast, stick B in the bottom of Figure 1 looks closer in length to the goal stick than sticks A and C. Thus, participants will pick stick B and subtract segments until the goal stick is achieved.

Of the 80 BST problems, 40 problems appeared biased towards overshoot and 40 problems were biased towards undershoot. This cue was manipulated to be successful 70% of the time—the predictiveness of the relative length cue remained constant across both conditions. Table 1 summarizes how problem types were manipulated over time for all participants (in both conditions)—overshoot success rate being changed over time, while the predictiveness of the length cue was held constant over time.

Table 1. Overshoot success rate and predictiveness of the length cue over blocks of trials (in both conditions).

Predictive cue	Trials 1-40	Trials 41-80
Overshoot success rate	70%	30%
Predictiveness of length cue	70%	70%

Consistent with the RCCL account, participants in the BST tend to report a variety of strategies (Lovett & Schunn, 1999). The two most salient strategies are the hill-climbing and exclusive strategies. In the hill-climbing strategy, participants compare the goal stick to the building sticks and select the stick that most closely matches the length of the goal stick. In the exclusive strategy, participants simply select one approach, overshoot or undershoot, without regard to which appears to be closest to the goal. As long as hill-climbing distance is predictive of solution success (as it was in the current experiment), the hill-climbing strategy is more likely to be successful than the exclusive strategy. However, the hill-climbing strategy also involves more effort because of the visual comparison component. Which strategy participants adopt across conditions will be the second primary dependent measure.

This task is a complex problem solving situation (according to the definition given in the introduction) because there is not a simple mapping between strategies and external alternatives. Table 2 presents the choices that participants would tend to make in each of the blocks under the hill-climbing and exclusive strategies. The exclusive strategy should tend to select the most successful approach regardless of what the problem looked like. By contrast, the hill-climbing strategy should tend to select approaches according to problem appearance, independent of the base-rate of success of each approach.

Table 2. Expected modal approach (O=overshoot, U=undershoot) under each strategy in each block for undershoot and overshoot biased problems.

	Trials 1-40		Trials 41-80	
Strategy	O-biased	U-biased	O-biased	U-biased
Hill-climbing	O	U	O	U
Exclusive	O	O	U	U

Procedure

Participants were randomly assigned to one of two conditions. In the Unpaid condition (the control group), participants received course credit only. However, in the Paid condition (the motivated group), participants received compensation in addition to course credit. Payment was based on a $10 scale and calculated according to the percentage of problems solved correctly within 5 steps or less. That is, participants who solved 80% of the problems in so few steps received $8.00 while participants who solved 60% of the problems in this way received $6.00.

At the beginning of the experiment, a computer tutorial provided participants with step-by-step instructions to the task, along with an animated demonstration of the undershoot and overshoot approaches. For participants in the Paid condition, the last page of the instructions informed the participants that they were being compensated for their participation based on their performance on the task. The instructor reiterated this to ensure participant motivation.

Predictions

The hill-climbing strategy is a more successful but more effortful strategy than the exclusive strategy. Therefore, RCCL predicts that the motivation manipulation should increase the participants' use of the hill-climbing strategy. Let us define base rate sensitivity as the difference in frequency of overshoot approach use from the first to second halves of the experiment. Then, because the exclusive strategy is more sensitive to the base-rates of overshoot and undershoot, RCCL predicts no effect of the motivation manipulation (or perhaps a decrease) on base-rate sensitivity, at least as defined in terms of external choices. By contrast, non-representational accounts (and perhaps even common sense) would suggest that the participants given the performance incentive should show greater base-rate sensitivity.

Strategy Coding

At the end of the Building Sticks Task, participants were asked about what strategies they used. Responses were classified into one of 5 categories: using whatever the problem looked like (hill-climbing), always using one stick size first (exclusive), using what worked previously (memory), randomly selecting sticks (trial and error), and other strategies (miscellaneous). Based on a recoding of 20% of the data by a second coder, the reliability for this coding scheme was 93%.

Results & Discussion

Verifying Differences in Strategy Features

The predictions of strategy shifts rest on assumptions about the differential effort and success rates associated with the various strategies. The assumptions were tested by examining the relationship between 1st mentioned strategy and participant mean success rates (across all blocks) and mean time to make the first move on each trial (across all blocks). Note that time to execute the strategy is used as an approximation of the effort required by a strategy. We expect that the participants using the hill-climbing strategy should be more successful and require less time to make choices. However, given that participants in this task have been found to typically each use several strategies during the course of the session (Lovett & Schunn, 1999), one would expect analyses averaging performance data across the whole session to show diluted trends.

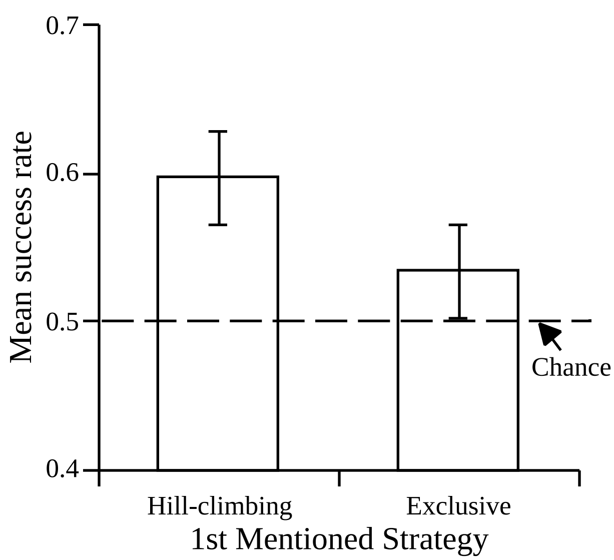

Figure 2. Mean success rate (and SE bars) for the hill-climbing and exclusive strategies.

Overall, there was a significant effect of 1st strategy mentioned on the mean success rates, $F(2,54)=8.8$, $MSE=0.004$, $p<.005$ (see Figure 2). Specifically, exclusive strategies (n=10) showed lower success rates than hill-climbing strategies (n=46). This trend was consistent within both conditions.

Overall, the timing data was more variable, with a non-significant overall effect of 1st strategy mentioned on the mean times to make the first move $F(2,54)=2.1$, $MSE=1.31$, $p>.15$ (see Figure 3). However, exclusive strategies did show the expected lower mean times than did hill-climbing strategies. This trend was consistent within both conditions.

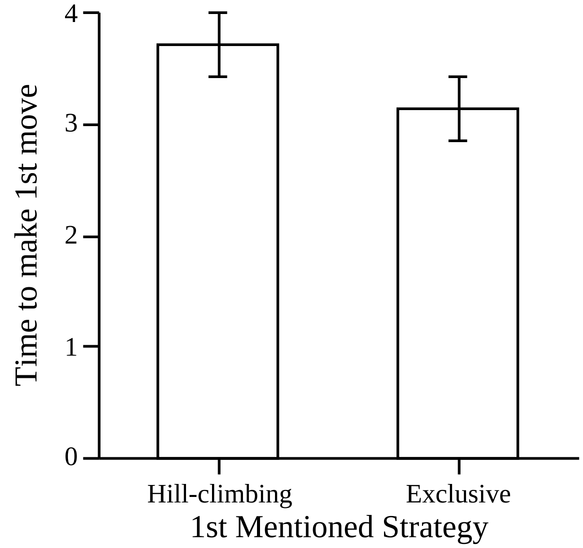

Figure 3. Mean time to make 1st move on each problem (and SE bars) as a function of the 1st mentioned strategy.

In sum, the assumptions about the differential effort and success rates between the hill-climbing and exclusive strategies were at least qualitatively supported.

Strategy Changes

Table 3 presents the frequency of mention of each strategy type based on the first strategy mention. We see the predicted increase in the use of hill-climbing strategy and the predicted decrease in the use of the exclusive strategy.

Note also that the Memory strategy, a relatively effort intensive strategy, showed an increase in the Paid condition, and that the Trial & Error strategy, a relatively effort free strategy showed a decrease in the Paid condition. The predicted increase in reliance on effortful strategies was statistically significant, $t(81)=1.6$, $p<.05$ (one-tailed).

While these effects were not large, it is important to note that these analyses are likely to be an underestimate of the effects¾participants did not indicate how often they used the mentioned strategies, and they do try multiple strategies.

Table 3. Proportion of participants mentioning each strategy within each condition.

Strategy	Unpaid (N=42)	Paid (N=41)
Hill climbing	0.50	0.61
Exclusive	0.17	0.07
Memory	0.10	0.15
Trial & Error	0.17	0.15
Misc.	0.07	0.02

Another important issue raised by RCCL is whether motivation has an impact on the degree of search for an optimal strategy. Towards this end, we examined the effect of condition on number of different strategies mentioned. There was no significant effect of condition on the number of strategies mentioned, F(1,81)<1. Both the Paid and Unpaid participants mentioned a mean of 1.4 strategies per participant.

Overall Base-Rate Changes Over Time

Both groups showed a rise in the amount of Overshoot use in the first half followed by a drop in the second half F(3,243)=16.6, MSE=0.015, p<.0001 (see Figure 4). There was no main effect of condition, F(1,81)<1, nor was there a significant interaction, F(3,243)=1.0, MSE=0.015, p>.3. To directly quantify the influence of condition on base-rate adaptivity, one can define base-rate adaptivity as the amount of drop in Overshoot use from the first half to the second half (difference of half means). On that measure, both Paid and Unpaid participants shifted exactly 7% in their use of Overshoot over time. As Figure 4 reveals, if anything, Paid participants were less sensitive to the base-rates. Thus, as predicted by RCCL, motivation manipulations produced changes in strategy use, not changes in base-rate sensitivity.

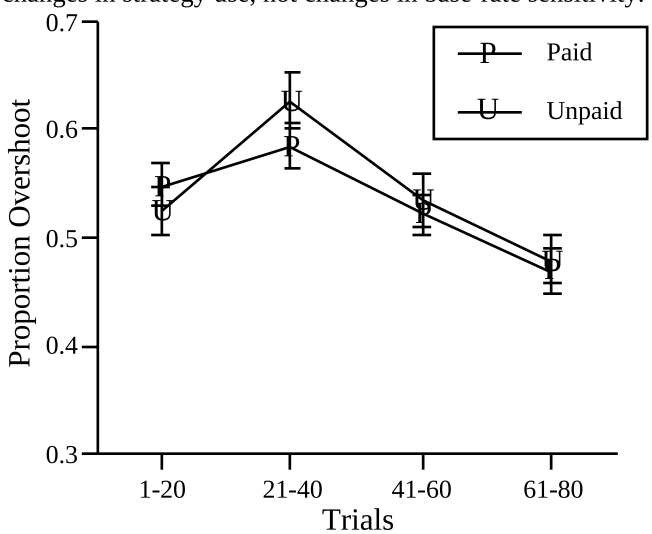

Figure 4. Proportion of overshoot choices within each set of twenty trials within each condition.

Hill-climbing sensitivity

One can also analyze the effects of problem appearance (whether the problem appearance was biased towards overshoot or biased towards undershoot) on solution method and its interaction with condition and blocks. As one always finds in this task, there are large effect of problem appearance on the proportion of overshoot selections, F(1,81)=657.0, MSE=0.038, p<.0001. More interestingly, there was also a significant interaction of appearance with condition, F(1,81)=6.5, MSE=0.038, p<.02. In particular, Unpaid participants showed a significantly lower sensitivity to problem appearance than did the Paid participants (49% versus 60% differences between overshoot-biased and undershoot-biased problem types).

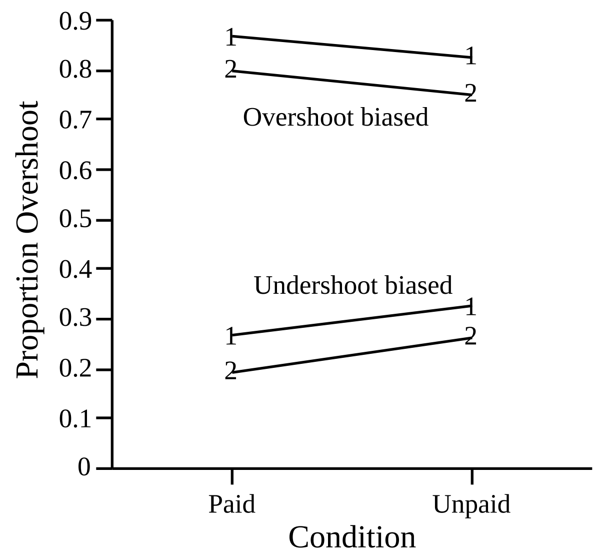

Figure 5. Proportion of overshoot choices as a function of problem appearance (Overshoot biased /Undershoot biased) and condition (Paid/Unpaid), for the first (1) and second (2) halves of the experiment.

This effect establishes that the payment manipulation did have some influence on participants, and thus clarifies the interpretation of the null effects on base-rate sensitivity. This effect is also consistent with increases in hill-climbing strategy use as a result of the manipulation.

General Discussion

This experiment found that increasing motivation levels can produce strategy changes (as measured by self-report and patterns in choice) without producing changes in base-rate sensitivity. The changes in strategy choice were consistent with a shift in motivation levels—a shift from lower-success/lower-effort strategies to higher-success/higher-effort strategies. Thus, the key predictions of the RCCL framework with respect to the effects of motivation levels on choice patterns were met. These findings are not consistent, by contrast, with non-strategy-based theories of choice that focus entirely on external alternatives rather than internal representations and strategies.

It should be noted that RCCL is a general framework, not a detailed model. With respect to the predictions regarding the effects of motivation, there are several particular utility-based strategy models of choice processes that could be used to account for the obtained results, including ACT-R (Anderson & Lebiere, 1998), SAC (Schunn, Reder, Nhouyvanisvong, Richards, & Stroffolino, 1997), and ASCM (Siegler & Shipley, 1995).

Some of the results of the current experiment are potentially difficult to interpret because they involve null effects of a manipulation. However, the manipulation did produce some effects demonstrating that it was strong enough to influence behavior. Moreover, it is somewhat rare to find a case in which performance in a problem-solving task does not improve when undergraduates normally taking part only for course credit are suddenly paid for higher performance levels.

Our experiment is also not the first to find no effect of motivation manipulations on base-rate sensitivity. For example, Goodie and Fantino (1995) found no effect of a motivation manipulation on base-rate sensitivity. They also used conditions of course credit and pay versus course credit alone, although they paid their participants as much as $40. While Goodie and Fantino did not explain their null result (it was also not the focus of their experiment), RCCL provides a potential explanation. The key is to examine whether the motivation manipulation produced changes in strategy use rather than changes in choices at the level of simple external alternatives. While the task used by Goodie and Fantino was not a complex problem-solving task, Lovett and Schunn (1999) established that participants do use a wide variety of strategies during that choice task as well.

Another consequence of the current experimental findings is that they resolve a question about individual differences. In particular, previous research on individual differences in sensitivity to base rates (Schunn & Reder, 1998; Stanovich & West, 1998) left open the possibility that the differences were due to motivational differences. The current research suggests that the observed individual differences in base-rate sensitivity are not so easily attributed to motivational differences.

The current experimental findings also permit some refining of the RCCL framework. RCCL posits that people will search for new representations and strategies when the success rates of the current alternatives are too low. An open question was whether motivational levels entered into determining when a search for new representations and strategies was begun. The current findings suggest that motivation levels do not have a large role of in the amount of search for alternative representations and strategies. Or, at least, all of the participants were sufficiently motivated to conduct such searches.

As a final note, the current experiment only manipulated one kind of motivation: extrinsic motivation. There are other types of motivation. For example, research (e.g., Button, Mathieu, & Zajac, 1996) has shown that people also differ in terms of their performance motivation (the degree to which they need to succeed) and learning motivation (the degree to which people prefer to learn new things). It is an open question whether those dimensions of motivation will have similar influences on choices processes generally, and base-rate sensitivity in particular.

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