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Fast or Rational? A Response-Times Study of Bayesian Updating

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We present a simple model for decision making under uncertainty building on dual-process theories from psychology, and use it to illustrate a possible component of intuitive decision making of particular relevance for managerial settings. Decisions are the result of the interaction between two decision processes. The first one captures optimization based on Bayesian updating of beliefs. The second corresponds to a form of reinforcement learning capturing the tendency to rely on past performance. The model predicts that (i) in the case of conflict between the two processes, correct responses are associated with longer response times, but (ii) if both processes are aligned, errors are slower. Furthermore, (iii) response times in the case of conflict are longer than in the case of alignment. We confirm the predictions of the model in an experiment using a paradigm where an associative win-stay, lose-shift process conflicted with rational belief updating.

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1. Introduction

When should you "trust your gut"? A long-standing discussion in management science concerns the value of intuitive decision making for day-to-day and business decisions. Arguments in favor of intuitive decision-making styles are often colorfully illustrated with examples where well-known chief executive officers "went with their gut." For today's harried executives, intuitive decisions have the advantage of being fast and effortless, hence freeing resources for other tasks. In recent years, many popular (management) science books have defended the value of intuition (e.g., Klein 2004), and some have gone so far as to praise the virtues of quick (even split-second) decision making over careful deliberation (Gladwell 2005). The debate often surfaces in different domains, ranging from discussions in the applied management literature (see, e.g., Hayashi 2001, Bonabeau 2003) to more psychologically founded accounts (Hogarth 2001). Recently, the sober text of Kahneman (2011) has started to raise popular awareness about this debate.[1]

A scientifically founded discussion on the virtues of different managerial decision-making styles requires a formal concept of intuition. Such a definition is absent in the economic sciences, which have been shaped by the assumption of fully rational decision makers. Psychology, however, has developed models and techniques enabling the discussion and measurement of the intuitive part of decision making. A theoretical scaffolding is delivered by *dual process theories*, which range from early examples in economics (Thaler and Shefrin 1981) to extensive psychological accounts (Kahneman 2004, Strack and Deutsch 2004). They postulate that the human mind is influenced by two broad kinds of decision processes. The first type, often called impulsive or *automatic processes*, are thought to be fast, immediate, effortless (i.e., placing low or no demands on cognitive resources), and requiring no conscious control. They are involved in many judgmental heuristics and are likely to cause behavioral biases (see, e.g., Ferreira et al. 2006). The second type, often called reflective or *controlled processes*, are described as slower, not immediate, at least in part consciously reflected upon, and consuming cognitive resources (Bargh 1989).[2]

[1] See also the debate in Kahneman and Klein (2009). These authors also discussed the perils of intuition for senior executives in a joint interview in *McKinsey Quarterly* (2010).

[2] Economics has also introduced multiple-selves models of decision making, which are inspired by dual-process theories, especially in the realm of intertemporal choice (Bernheim and Rangel 2004, Benhabib and Bisin 2005, Fudenberg and Levine 2006).

A large part of what is commonly understood as "intuition," following the psychological literature (see, e.g., Glöckner and Witteman 2010), can be broadly conceived as the collection of automatic processes available to a decision maker. Those might include fine-tuned, automatized processes that capture years of managerial experience (this is actually what is reflected in most examples in Gladwell 2005). However, they might also include many basic cognitive shortcuts (heuristics) that, although often delivering correct responses in a short time (and hence being seen as seductively efficient in the workplace), might occasionally lead to disastrously wrong decisions.

These theoretical underpinnings deliver a host of techniques allowing for quantitative measurements of whether a decision is more or less intuitive, i.e., corresponds to a more intuitive/automatic process. The first and simplest method is the experimental measurement of response times, i.e., the time from presentation of the new information till a decision is reached. Since automatic processes are quicker, they generate faster responses, and hence hypotheses on the nature of decision processes deliver predictions on response times; that is, response times become a useful tool to quantify assertions on the intuitive character of decisions and hence can contribute both to the analysis of different decision-making styles and to the identification of the intuitive roots of costly mistakes.[3]

In this paper, we use response times to evaluate a dual-process approach for *decision making under uncertainty* when new information arises as feedback from previous decisions. We postulate that decision making in such situations can be understood as the result of the interaction between two kinds of decision processes, an automatic one reflecting intuitive principles and a controlled one corresponding to more "rational" behavior. It is worth noting that, until now, only some dual-process accounts have explicitly addressed decision making under uncertainty (a recent exception is Mukherjee 2010). Our approach bears similarities to the one of Rottenstreich and Hsee (2001) and Hsee and Rottenstreich (2004), who suggest that the valuation of choices might be assessed through both an affective valuation by feeling and a deliberative valuation by calculation.

In this context, there are natural choices of controlled and automatic processes to focus on. Consider the former. Optimal decision making under uncertainty involves the integration of preexisting information with that obtained from recent decisions. The rationality benchmark postulates an optimizing agent endowed with a subjective probability distribution (belief) on uncertain events. Whenever new information on these events is provided, the agent should adjust the prior according to Bayes' rule;[4] that is, the rational paradigm leads to optimizing behavior based on *Bayesian updating of beliefs*, which we will identify with a controlled process for modeling convenience.

As an automatic process, we will focus on the fact that many economic decisions, especially in the business world, lead to clearly quantifiable feedback, in the form of profits or losses, reached or missed objectives, and positive or negative comparisons with a reference point, be it the previous quarter's sales or the relative position in a business ranking. The association of success or failure to the original decision creates a tendency to rely on *past performance* as an indicator of future outcomes. A given decision will tend to be repeated if it led to success in the past, and to be changed if it led to failure. This is captured by *reinforcement learning* (Sutton and Barto 1998, Erev and Roth 1998),[5] which, in its simplest form, corresponds to a "win-stay, lose-shift" associative heuristic, which simply prescribes to repeat the previous decision whenever successful. Associative rules are naturally automatic (Sloman 1996, Strack and Deutsch 2004, Bayer et al. 2009), and hence we will focus on reinforcement as the natural automatic process in our context.[6]

Reinforcement processes are important for managerial decision making, because repeating whatever worked in the past might be a cognitive shortcut to optimal behavior in many situations. In a complex world, however, successes and failures deliver

Furthermore, the consideration of dual-process approaches is slowly starting to influence experimental paradigms in behavioral economics (see, e.g., Cappelletti et al. 2011).

[3] Although the measurement of response times (also called *latencies*) is a standard tool in psychology (we refer the interested reader to Bargh and Chartrand 2000 as a starting place), it has been used only occasionally in economics. To our knowledge, the first studies employing "decision times" in economics were those of Wilcox (1993, 1994), who related them to decision costs in the context of risky choice (see also Moffatt 2005). More recently, Piovesan and Wengström (2009) measured response times in a dictator game. Rubinstein (2007) advocated the measurement of decision times in large-scale, Web-based experiments. Response times have also been used in recent neuroeconomics studies such as, e.g., Krajbich et al. (2010) or Achtziger et al. (2013).

[4] We use the word "rationality" in this particular sense. For a detailed discussion of rationality under uncertainty, see Oaksford and Chater (2007).

[5] The stimulus-response formulation of reinforcement learning can be traced back to the "law of effect" (Thorndike 1911), and it has been extensively studied in psychology. Reinforcement learning has also received a great deal of attention in game theory (see, e.g., Roth and Erev 1995, Börgers and Sarin 1997). For a broader perspective on reinforcement learning, see Chater (2009).

[6] Research in neuroscience has provided a neurobiological basis for reinforcement learning as an automatic decision process (Schultz 1998). Holroyd and Coles (2002) conclude that reinforcement learning is associated with extremely fast and unconscious brain responses, the very mark of automatic processes.

both payoffs and information, and those might be at odds. Baron and Hershey (1988) showed that the evaluation of decisions tends to be heavily anchored on outcomes (even if those have a large random component), neglecting other available information. This "outcome bias" has been shown to have negative consequences for the evaluation of managers and learning in organizations (see, e.g., Dillon and Tinsley 2008). For instance, suppose regional manager A obtains much better end-of-year results than regional manager B. This feedback might motivate a decision to fire manager B. However, this decision ignores both previous information (the prior) and the fact that the regional results are indicative of local market conditions. A proper analysis might reveal that manager B was facing much harder conditions and the rational decision might even be to move him to the region of manager A.

Our strategy of research is both analytical and experimental. First, we develop a simple, parsimonious dual-process model of decision making and formally derive clear-cut predictions on the interaction of speed and accuracy (§2). Our model helps structure experimental data and also delivers novel predictions in the domain of decision making under uncertainty. We then test the predictions of the model in an experiment on decision making and belief updating (§§3 and 4). Our paradigm is meant to be stylized but still representative of problems faced by decision makers in economics and management, i.e., where prior and new information need to be integrated, but previous decisions also deliver a success/failure feedback possibly triggering a reinforcement heuristic. For this purpose, we build upon a binary-choice paradigm first introduced by Charness and Levin (2005) where Bayesian updating conflicts with reinforcement learning, and this conflict helps explain the pattern of decision mistakes. Specifically, participants are endowed with a prior on an uncertain event and are asked to make a decision *twice*. The first time the decision is made, binary feedback (success/failure) results. By its very nature, this feedback might act as a trigger for reinforcement learning. However, it also carries information on the underlying uncertain event and allows updating beliefs to make a better second decision. Depending on certain circumstances, the prescriptions of reinforcement and Bayesian updating might be the same or opposite ones.

Our analysis shows that the qualitative features of process data (and, specifically, response times) associated to decisions in this paradigm are accurately predicted by a stylized dual-process model of intuitive biases in decision making. Our results are consistent with the interpretation that a focus on past performance can be viewed as a part of intuitive decision making. This is especially relevant for managerial decision settings, where optimal decision making requires the careful integration of past and new information, but information frequently comes with a success/failure frame.

The model and the experimental data also deliver additional insights. It is intuitive that balanced, well-thought-out decisions require time, especially if they require the integration of prior and new information. Since the decision processes underlying impulsive behavior are generally quick, one might also intuitively expect slow decisions to be always better, in analogy with the speed-accuracy trade-off found in many psychophysical tasks. We show (both formally and experimentally) that this account may be false. In particular, whenever both processes prescribe opposite answers, errors do tend to be quicker, but whenever the initial tendencies of both processes are aligned, errors tend to be slower. This at first glance counterintuitive prediction (which is also observed in our data) is, we show, a logical consequence within a formal dual-process model.

We have focused on reinforcement learning due to the importance of past performance for economic and managerial decision making. The experimental paradigm we have used is designed to isolate this particular phenomenon. Our model and general approach, however, are also potentially relevant beyond this paradigm. Specifically, the formal predictions apply to any impulsive process that competes with Bayesian updating or another controlled process. This includes well-documented phenomena leading to systematic violations of Bayes' rule as reported both in psychology and in economics, e.g., the representativeness heuristic (Kahneman and Tversky 1972, Grether 1980, Camerer 1987) and the more general phenomenon of base-rate neglect (see, however, Fiedler et al. 2000, Erev et al. 2008), the conjunction fallacy (Tversky and Kahneman 1983, Zizzo et al. 2000), and many others. Many of those can be conceived as the result of impulsive processes that occasionally conflict with Bayesian updating (see, e.g., Achtziger et al. 2013). In fact, El-Gamal and Grether (1995) showed that, even when the representativeness heuristic is present, Bayes' rule is still the most likely rule (but not the only one) used by humans in probability updating (see also Griffiths and Tenenbaum 2006, 2011). This multiplicity of decision processes of different character fits the dual-process approach we advocate in this article.

In spite of these potential generalizations, our paradigm abstracts from a number of factors that are also relevant for the study of intuitive decision making. First, our research concentrates on a particular feature of decision making under uncertainty, i.e., learning and updating of beliefs. There are other parts of the decision process that might be affected by "intuitive" behavior leading a decision maker astray, such as, e.g., framing effects (Tversky and Kahneman 1981) or incorrect assumptions about priors (Erev et al. 2008).[7] Second, we have considered a setting with objectively given priors. When those are absent or need to be learned or estimated, a host of other processes also play a role in intuitive decision making. For instance, the literature on decisions from experience (e.g., Myers and Sadler 1960, Hertwig et al. 2004, Erev and Barron 2005) relies on paradigms where the probabilities of events have to be learned in the course of many decisions. Within the related domain of probabilistic inferences under uncertainty, Fiedler and Plessner (2009) present a taxonomy of inductive processes, which are conceived as "bottom-up," stimulus-driven processes in contrast to deductive ones, which are "top-down" and knowledge driven.

2. A Simple Dual-Process Model

We first present our formal model in as concise a way as possible, and then discuss the dual-process rationale behind the model's assumptions. Then we formally derive our predictions, which will deliver natural hypotheses for the experimental part of the study.

2.1. The Model

We consider a decision with two available choices, to be made on the basis of prior information. Two processes can be involved in determining the decision, an automatic, reinforcement-based one ($i = A$) and a controlled one, which proxies Bayesian updating of beliefs ($i = C$). The response time of a process, $RT_P(i)$, is stochastic. The automatic process selects a response with expected response time $T_A = E[RT_P(A)]$, and the controlled process one with expected response time $T_C = E[RT_P(C)]$.

Assumption 1. *The expected response time of the automatic process, T_A, is strictly shorter than that of the controlled process, T_C, i.e., $T_A < T_C$.*

Both processes are stochastic, and each of them can select each possible response with positive probability. The response with the highest probability for a process is called the response *favored* by that process. The automatic process favors the response that follows from a win-stay, lose-shift heuristic. This response is selected by the automatic process with probability $1/2 < P_A < 1$. In contrast, the controlled process always favors the correct response, i.e., the one derived by Bayesian updating of beliefs. Specifically, the controlled process selects the correct response with probability $1/2 < P_C < 1$. The automatic process is swifter in the sense that it has a lower rate of nonfavored responses.

Assumption 2. *The probability that the automatic process selects its favored option, P_A, is strictly larger than the probability that the controlled process selects its favored option, P_C, i.e., $P_A > P_C$.*

If both processes favor the same response, we speak of *alignment*. If they favor different responses, we speak of *conflict*. The actual response may come from either process. A central executive function governs the selection of the process that actually selects a response. This process selection is sensitive to whether there is a conflict or not. The automatic process is selected with a probability $\Delta = \Delta_1$ (in case of conflict) or $\Delta = \Delta_0$ (in case of alignment). Hence,

$$\text{Prob}(Correct \mid Conflict) = (1 - \Delta_1) \cdot P_C + \Delta_1 \cdot (1 - P_A),$$

$$\text{Prob}(Correct \mid Alignment) = (1 - \Delta_0) \cdot P_C + \Delta_0 \cdot P_A.$$

Assumption 3. *The controlled process is more likely to be selected in case of conflict than in case of alignment, i.e., $0 < \Delta_1 < \Delta_0 < 1$.*

Furthermore, conflict resolution is time consuming. Process selection increases total response time in $RT_S(e)$, where $e = Alignment$ if both processes are aligned and $e = Conflict$ if they are in conflict.

Assumption 4. *Conflict resolution is time consuming; i.e., in case of conflict, process selection takes longer: $E[RT_S(Conflict)] > E[RT_S(Alignment)]$.*

Total response time can be decomposed as follows:

$$RT = RT_S(e) + RT_P(i),$$

where e indicates whether processes are aligned or in conflict, and i is the process actually selected.

2.2. Model's Rationale

Following dual-process theories,[8] an automatic process is based on a fast and effortless heuristic or associative thought routine that delivers a quick response to stimuli on the basis of previous learning experiences. In contrast, a controlled process incorporates deliberation, and hence is more flexible, but also slower and noisier, i.e., it delivers an unexpected result more often.

For modeling purposes, we consider a decision process to be a thought routine that, when confronted with a decision problem, delivers an answer and a

[7] As pointed out by a referee, correctly applying Bayesian updating to the incorrect model is a real-world source of mistakes that might help explain the predominance of belief-free cognitive shortcuts as reinforcement learning.

[8] The literature on dual processes is extensive. We refer the reader to Rustichini (2008), Evans (2008), and Weber and Johnson (2009) for reviews, and to Evans and Stanovich (2013) for a recent discussion.

response time. Each of the two processes has a tendency to favor one of the choices given the available information. The automatic process reflects "win-stay, lose-shift," and hence favors choices that delivered good results in the past, which might currently be optimal or not. In contrast, the controlled process tends to select the correct response given all available information.

Since decision making and information accumulation are stochastic in nature, we assume that each process might select its nonfavored choice with a certain probability (smaller than 1/2). This results in our Assumptions 1 and 2. Assumption 1 simply reflects that the expected response time of an automatic process should be shorter than that of a controlled process. Assumption 2 captures the interpretation of an automatic process as a quick, efficient routine, which implies that the probability with which it selects its nonfavored choice should be smaller than in the case of the controlled process.[9]

In a conflict situation, by definition, an automatic process is likely to select a suboptimal response, which is opposed to the one selected by the deliberative process. Examples range from making the wrong turn at an intersection out of habit when driving to a new place to concentrating on a single salient attribute (e.g., low price) when choosing among several alternative consumer goods. In the opposite case, both processes might be aligned. For example, in a stable decision environment, a simple behavioral rule based on blindly repeating or imitating successful behavior can be a cognitive shortcut to optimal behavior ("fast and frugal heuristic"; Gigerenzer and Goldstein 1996).

Following research on working memory (Norman and Shallice 1986; Baddeley 1996, 2012), we postulate a central executive system that mediates which process determines the final decision. Process selection is sensitive to the presence of a conflict.[10] Specifically, conflict resolution reduces to the assumption that the central executive intervenes to inhibit automatic processes and enable controlled processes to proceed instead. This is captured by Assumption 3. In our model, the process selection probability Δ describes the result of the supervisory function undertaken by the central executive. Hence, the assumption is that the automatic process is selected with a lower probability in case of conflict, $0 < \Delta_1 < \Delta_0 < 1$.

Whenever two decision processes conflict, the central executive is engaged, and cognitive resources are taxed, resulting in longer response times than when no conflict exists;[11] that is, conflict resolution is time consuming (MacCleod 1991, Botvinick et al. 2001, De Neys and Glumicic 2008). It is important to note, however, that this feature is independent of the assumption that automatic processes are quicker (Assumption 1). This is captured by Assumption 4.

Summarizing, the intuition of the model is as follows. An automatic process is a quick heuristic converting a stimulus into a response in a fast and effective way, due to former learning experiences in similar situations. Hence, it leads to the favored response (say, flee if attacked) with a high probability and in a short time whenever the appropriate cues are present. Depending on the situation, however, the favored response can be correct or not. In our setup, the favored option of the controlled process is always correct. This process incorporates some (noisy) deliberation, and hence is slower and might result in an unexpected result (not selecting the favored action) more often than the automatic process. In case of conflict, the automatic process favors the opposite answer to the controlled one, which quickly results in an error. In case of alignment, the automatic process also favors the correct response and delivers a choice more quickly than the controlled process. Last, a central executive system supervises process selection. The task of this system is to intervene in case of conflict, increasing the probability that the controlled process is the one that ultimately selects the answer. However, this intervention is time consuming and results in increased response times.

2.3. Model's Predictions

The model described above allows us to derive several clear-cut predictions. The first two concern expected differences in response times between correct responses and errors, conditional on either conflict or alignment.

Proposition 1. *In case of conflict, the expected response time of a correct response is strictly longer than*

[9] A referee has pointed out that our Assumption 2 can also be linked to overconfidence, since it implies that the more deliberative process has a nonnegligible failure rate.

[10] Some dual-process theories implicitly assume a supervisory system that selects a process (e.g., as a part of the reflective system governing controlled processes). The exact mechanisms of process selection, however, remain unclear at this point. One could imagine that the central executive supervises the evolution of the processes in time and determines whether they evolve in the same direction or not. Our model simply postulates that whether there is a conflict or not influences process selection, but remains silent on the mechanisms behind this selection.

[11] One illustrative example is provided by the Stroop effect (Stroop 1935, MacCleod 1991), which refers to the phenomenon that the ability to name the ink color in which a word is printed is inhibited if that word names a conflicting color. For example, if the word "red" is printed in blue ink, it is difficult to name the ink color (blue) without suffering some interference, which produces a slowdown of response times. One explanation is that reading a word is an automatic process that needs to be inhibited, whereas naming the color is a more controlled process.

the expected response time of an error. In case of alignment, the expected response time of an error is strictly longer than the expected response time of a correct response.

Proof. Consider first the case of alignment. The expected response times are

$$E[RT_P \mid Correct, Alignment] = ((1-\Delta_0)\cdot P_C\cdot T_C+\Delta_0\cdot P_A\cdot T_A)/(P(Correct \mid Alignment)),$$

$$E[RT_P \mid Error, Alignment] = ((1-\Delta_0)\cdot(1-P_C)\cdot T_C+\Delta_0\cdot(1-P_A)\cdot T_A)/(1-P(Correct \mid Alignment)),$$

and a computation shows that $E[RT_P \mid Error, Alignment] > E[RT_P \mid Correct, Alignment]$ holds if and only if $T_A(P_C - P_A) > T_C(P_C - P_A)$. Since $P_A > P_C$ by Assumption 2, the condition reduces to $T_A < T_C$, which holds by Assumption 1. Hence, errors are slower.

Turn now to the case of conflict. The expected response times are

$$E[RT_P \mid Correct, Conflict] = ((1-\Delta_1)\cdot P_C\cdot T_C+\Delta_1\cdot(1-P_A)\cdot T_A)/(P(Correct \mid Conflict)),$$

$$E[RT_P \mid Error, Conflict] = ((1-\Delta_1)\cdot(1-P_C)\cdot T_C+\Delta_1\cdot P_A\cdot T_A)/(1-P(Correct \mid Conflict)),$$

and a computation shows that $E[RT_P \mid Error, Conflict] < E[RT_P \mid Correct, Conflict]$ holds if and only if $T_A(P_C-(1-P_A)) < T_C(P_C-(1-P_A))$. Since $1-P_A < 1-P_C < P_C$ (the last inequality holds because $P_C > 1/2$), the condition reduces to $T_C > T_A$, which holds by Assumption 1. Hence, correct responses are slower. □

The intuition behind this proposition is as follows. Suppose the task is repeated time and again. In conflict situations, the automatic process favors the incorrect answer, whereas the controlled process favors the correct one. Hence, most correct answers come from the controlled process and are slower. The conclusion in alignment situations might seem counterintuitive at first. However, since $P_A > P_C$, in this case the automatic process selects the incorrect answer with a smaller probability than the controlled process. Thus most responses generated by the automatic process are correct, and most errors are generated by the controlled (slower) process. Hence, response times conditional on incorrect responses tend to be longer in alignment situations.

This proposition yields two predictions, which in turn deliver experimental hypotheses:

Prediction I. In alignment situations, errors are slower.

Prediction II. In conflict situations, correct responses are slower.

A third qualitative prediction concerns the comparison of response times in case of alignment and conflict. The expected response times in case of conflict or alignment, independently of whether the response is correct or an error, are as follows:

$$E[RT \mid Conflict] = E[RT_S(Conflict)] + ((1-\Delta_1)\cdot T_C+\Delta_1\cdot T_A),$$

$$E[RT \mid Alignment] = E[RT_S(Alignment)] + ((1-\Delta_0)\cdot T_C+\Delta_0\cdot T_A).$$

Since $\Delta_1 < \Delta_0$ by Assumption 3 and $T_C > T_A$ by Assumption 1, it follows that $((1-\Delta_1)\cdot T_C+\Delta_1\cdot T_A) > ((1-\Delta_0)\cdot T_C+\Delta_0\cdot T_A)$. By Assumption 4, $E[RT_S(Conflict)] > E[RT_S(Alignment)]$. Hence, we obtain the prediction that $E[RT \mid Conflict] > E[RT \mid Alignment]$, which is compatible with received evidence in psychology and delivers the following hypothesis.

Prediction III. Situations with a decision conflict involve longer response times than alignment situations.

The next prediction and experimental hypothesis will concern a particular experimental treatment. Suppose that, in a given decision situation, we could remove the win/stay cues on which the automatic reinforcement process operates, i.e., the information was not presented in a win/loss frame. Call such a situation *neutral* (neither alignment nor conflict). Then, the automatic process, viewed as a stimulus-response routine, would not have a cue on which to operate. For all practical purposes, we can consider that this process is not activated, and all decisions follow from controlled processes. The expected response time in this case is simply $E[RT_P] = T_C$. Since the decision process conflict is absent both in case of alignment and in neutral situations, it is natural to assume $E[RT_S(Neutral)] = E[RT_S(Alignment)]$. It follows then that, for neutral situations, expected response times should be longer than in case of alignment, since, for the latter, $E[RT_P]$ is a convex combination of $T_A < T_C$ and T_C. These considerations yield the following prediction.

Prediction IV. Neutral situations involve longer response times than alignment situations.

This prediction is of course compatible with the more conservative assumption $E[RT_S(Neutral)] \geq E[RT_S(Alignment)]$, which might be justified if $RT_S(Neutral)$ captures process selection against additional automatic processes running in the background, as opposed to a single, salient automatic process aligned with the controlled one. Note, however, that no prediction can be made on the relationship between response times for neutral and conflict situations. Process time should again be longer in the case of neutral situations, but process selection time could be argued to be shorter, $E[RT_S(\mathit{Neutral})] < E[RT_S(\mathit{Conflict})]$. Whether one effect offsets the other remains an empirical question.

2.4. Model Extensions and Alternatives

We have intentionally kept our formal model as simple as possible. In this subsection, we briefly discuss some possible extensions and alternatives.

First, the model can be extended to incorporate a number of internal and external factors. A simple way is to consider variations in the probabilities of selecting the automatic process, Δ_0 and Δ_1. For instance, a common prediction of dual process theories is that controlled processes are selected less often when central executive functions are taxed, e.g., through cognitive load. This can be captured by modeling Δ_i as a decreasing function of the amount of available cognitive resources. Analogously, the model can be generalized to take monetary incentives into account. The natural economic hypothesis is that increased incentives result in increased performance, possibly through increased attention in the case of decision conflict. This could be captured by writing Δ_1 as a decreasing function of monetary incentives, implying that external incentives might increase the probability of selecting controlled processes in the case of conflict. However, it is well known that the relation between incentives and performance is far from straightforward (e.g., Camerer and Hogarth 1999), due, e.g., to ceiling effects for relatively complex tasks. Such complications could also be incorporated into the model by considering nonlinear functional forms, e.g., incorporating lower bounds (possibly different across individual decision makers) for Δ_1.

Second, our model can be given a "microfoundation" along the lines of process models in cognitive psychology, although this is not necessary for our purposes. In those models, a process is modeled as a stochastic diffusion process (Ratcliff 1978); the sign of the drift parameter indicates which option is favored. Suppose we model each of our processes as such a stochastic diffusion process. Endow the automatic process with a larger drift (in absolute value) than the controlled one, capturing the idea that it is "swifter." Then, one can derive explicit formulae for expected response times and probabilities of nonfavored responses. It can be proven that $T_A < T_C$ and $P_A > P_C$ must hold, i.e., Assumptions 1 and 2 become formal results (details are available upon request). A crucial difference with models in cognitive psychology, however, is that the processes do not systematically favor a given answer; rather, the tendency of the automatic process defines whether alignment or conflict occurs. This difference is natural. The model of Ratcliff (1978) is typically applied to perception, memory, and other tasks "on which response time is typically under a second" (Ratcliff and Rouder 1998, p. 347), and errors are mainly due to noise. In contrast, we study decision-making situations in which errors might arise from higher-level processes and response times are naturally longer.

Third, our formal model builds upon elements common to most dual-process theories and is hence compatible with different theoretical elaborations. It is interesting to consider, however, whether our main predictions could also be supported by theoretical accounts not relying on a dual-process formulation. We comment here on two possibilities.

Building on the diffusion-process microfoundation mentioned above, we could also postulate a single-process variant of Ratcliff (1978). It has been observed that this model can account for differences in the relative speeds of correct responses and errors by allowing its parameters, e.g., μ, to vary across the trials of a task (see Ratcliff 2013 for a recent discussion). In the original model, the drift parameter μ itself is normally distributed. However, as Ratcliff and Rouder (1998, Figure A) observed, if μ takes only two positive values, the expected time of the favored answer can be shorter than that of the alternative one, fitting Prediction I. Actually, a single process with two possible positive drifts selected randomly is equivalent to two randomly selected processes with different drifts, and hence this conclusion also follows from Proposition 1. This would enable a single-process reinterpretation of our model. The problem with this interpretation is that, to simultaneously fit Predictions I and II, i.e., the interaction of response times for correct and incorrect responses with conflict or alignment, the model would have to specify intertrial parameter variation in such a way that what we call alignment and conflict correspond to randomization among drift terms of the same or different signs, respectively. Hence, we find it more natural to interpret the two possible values of the drift parameter as two processes of different natures.

A notable criticism of dual-process theories has been given by Kruglanski and Thompson (1999) and, more recently, Kruglanski and Gigerenzer (2011) (we refer the reader to Evans and Stanovich 2013 and the comments on that article for a detailed discussion). These authors argue that what are conceptualized as automatic and controlled processes can have common roots and both be the result of *rules* processed by the same brain systems. Although the differences between this "unimodel" and standard dual-process theories are deep, they concern mostly the interpretation that different brain systems are responsible for different kinds of decision processes, which is not essential for our model. In fact, the conceptualization of Kruglanski and Gigerenzer (2011) rests on the possibility of rule conflict and rule selection. It is hence easy to recast our model in terms of conflict between an associative "win-stay, lose-shift" rule and a more complex rule conforming to optimization based on Bayesian updating of beliefs. Kruglanski (2013, pp. 244–245), however, views rule interaction as situations where a default response (in our case, that associated to reinforcement) is perceived as falling short of a confidence requirement, inviting further mental activity until the desired level of confidence is attained. If this interpretation were taken literally, it would imply that investing more time in a decision can only increase performance, which would be at odds with our predictions (specifically, the difference between Predictions I and II). However, it has to be mentioned that the model of Kruglanski and Gigerenzer (2011) makes no actual assumptions on the response times of different rules. Hence, we can reproduce our predictions in their framework simply by recasting our assumptions in terms of rules. If this step is made, though, the difference between rules and processes becomes purely semantic, at least for our purposes, and again we find it more natural to formulate our assumptions in terms of processes.

3. A Bayesian Updating Experiment

The basic experimental paradigms employed in economics to evaluate Bayesian updating can be described as variants of a "posterior probability task." Grether (1980, 1992) and El-Gamal and Grether (1995) introduced this kind of tasks to economics to study the *representativeness heuristic*, which had previously been observed in psychology (Kahneman and Tversky 1972). Such tasks can be described in terms of a binary choice problem. One of two possible covered urns $s = a, b$ will be used to extract balls with replacement. Hence the urn can be identified with an underlying state of the world. Urn a is selected with a commonly known probability p (induced as a prior). Urns contain N balls of two different colors, e.g., white and black. Urn a contains W_a white balls and $B_a = N - W_a$ black ones; urn b contains W_b white balls and $B_b = N - W_b$ black ones.

Participants know the prior p but not the urn from which the ball is extracted. They are shown one or several extractions from that urn (with replacement) and asked to guess which urn the ball(s) were actually taken from, or to perform some other task (e.g., belief elicitation) whose success depends on knowledge of which urn was used. A rational decision maker should update the prior p through Bayes' rule, using the information provided by the color of the extracted balls. For instance, if the first extracted ball is white, the updated belief that the employed urn was a should be $pW_a/(pW_a + (1-p)W_b)$.

3.1. The Reinforcement Heuristic

To test our model's predictions, we adapt a paradigm from Charness and Levin (2005). There are *two* urns, the left urn and the right urn, and both contain $N = 6$ balls, which can be black or white. Participants are asked to choose which urn a single ball should be extracted from (with replacement), and are paid if and only if the ball is of a prespecified color (say, black). Then they are asked to choose an urn a *second* time, a ball is extracted again, and they are paid again if the ball is of the appropriate color. The distributions of balls in the two urns vary depending on a common state of the world (up or down), which is determined (independently in each period) with a commonly known probability distribution (the prior). The state of the world is constant across the two draws. For the second draw, a fully rational decision maker should choose the urn with the highest expected payoff, given the posterior probability updated through Bayes' rule after observing the first ball's color.

Charness and Levin (2005) documented a systematic deviation from Bayes' rule, which we will refer to as the *reinforcement heuristic*. A decision maker following this heuristic will base his or her behavior on a simple "win-stay, lose-shift" rule of thumb: stay with the same urn as in the first round if it has delivered a success (black ball), and switch if not.

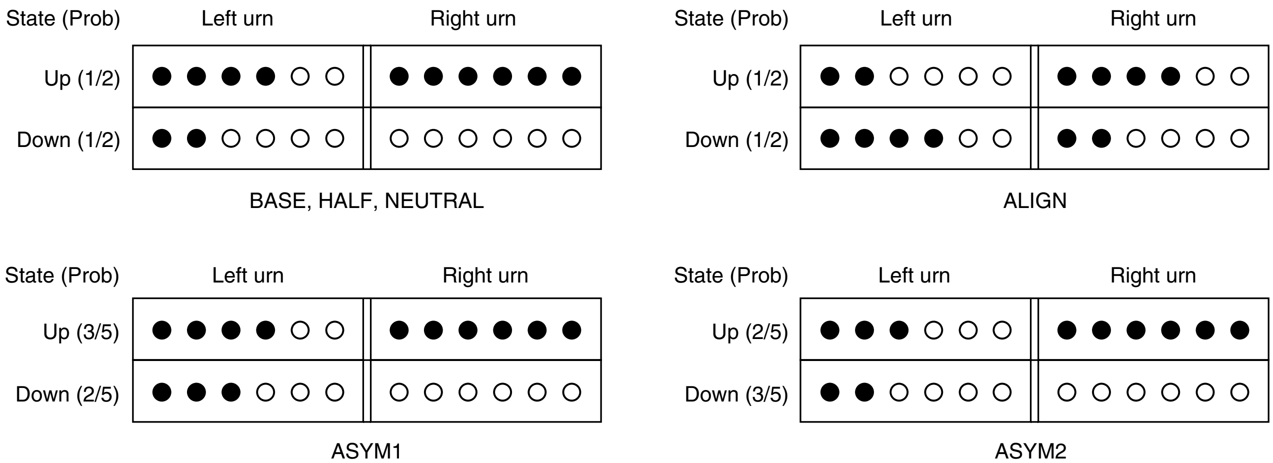
The essence of the experimental design is as follows. The right urn contains balls of one color only, different for each state of the world. Hence, choosing this urn reveals the state of the world. The left urn contains balls of both colors in both states, but the composition is such that if this urn is chosen first, the reinforcement heuristic and Bayesian updating select opposite choices (decision conflict). To guarantee a reasonable number of observations following left-urn choices, and following Charness and Levin (2005), the design includes "forced draws" in which participants do not have a choice for the first draw, but rather are forced to start alternatively with left and right.

We aim to use response times for testing the hypothesis that the reinforcement heuristic is a more automatic process than decisions following Bayesian updating. Moreover, we are also interested in manipulations such as, e.g., the effect of monetary incentives, and hence we introduce several treatments in the basic design as described below.

3.2. Experimental Treatments

3.2.1. Participants. One hundred and seventy-seven university students (95 males and 82 females) participated in exchange for performance-based

Figure 1 The Experimental Treatments



Note. An unknown state of the world (up, down) with a known prior (probabilities in parentheses) determines the composition of two urns (left, right) containing six balls each (black or white). All winning balls paid the same independently of which urn they came from.

payment. Three other participants were excluded from the analysis because they simply pressed keys obviously ignoring feedback.

3.2.2. Procedure. The experiment was computer-implemented using Presentation (Neurobehavioral Systems), a standard stimulus delivery and experimental control software platform designed to obtain the highest precision in stimuli presentation and time recording. A session lasted about 35 minutes, and average earnings were 10.72 euros. Data were collected individually, i.e., each participant was cited, instructed, and participated in the experiment individually; there were no other participants present. Participants received detailed written instructions, and all clarifying questions were answered. The experiment started after participants finished reading the instructions and all understanding questions were answered by the experimenter. There were no practice trials, no waiting times within the experiment, and no time pressure. After the experiment, participants filled in a questionnaire including demographic data (to be used in the regression analysis).

3.2.3. Treatments. Participants were randomly assigned to one of six treatments, with different urn compositions and initial priors (Figure 1). Each participant faced the two-draw decision 60 times. The state of the world was the same for the two draws within a round, but was randomized according to the prior for each new round. The color of the winning balls was counterbalanced across participants (for simplicity, we will speak of the winning balls as black). The payment per winning ball was 18 euro cents (except for treatment HALF).

Treatments BASE, HALF, ASYM1, and ASYM2 are the basic treatments, the only differences being that the priors in ASYM1 and ASYM2 are asymmetric, and that the payment per winning ball was set at 9 euro cents in HALF to test for possible incentive effects. In these treatments, the first-draw decisions in the first 30 trials were forced, alternating left and right, and the remaining first-draw decisions were free. Simple computations show that, after an initial choice of the left urn, Bayesian updating prescribes switching to the right urn after a winning ball and staying with the left urn after a losing ball, in exact opposition to a reinforcement heuristic. For example, in treatment BASE, if a black ball is extracted from the left urn, the updated probability of "up" is $((1/2)(2/3))/((1/2)(2/3)+(1/2)(1/3)) = 2/3$, hence choosing left again delivers an expected payoff of $(2/3)(2/3)+(1/3)(1/3) = 5/9$, whereas switching to right delivers a larger expected payoff of 2/3. Furthermore, the expected payoff, according to the prior, of choosing the left or the right urn for a single draw (uninformed choices), is identical. This guarantees that choices are not intrinsically biased.

Treatment ALIGN was a control treatment without decision conflicts, i.e., Bayesian updating always prescribes win-stay, lose-shift. Here, all first-draw decisions were free. Treatment NEUTRAL was as BASE with the difference that all first draws were forced (from left) and unpaid. Furthermore, the color of winning balls in the second draw was randomized across periods and communicated only after the first draw. This mechanism effectively removes *valence*, i.e., the possible emotional attachment to the black color because it results in a payment.[12] In turn, this

[12] The term *valence* arises in motivation psychology (Lewin 1939) and refers to a short-lived emotional attachment to certain events having a reinforcement value, but is unrelated to emotional states (mood). Charness and Levin (2005) refer to this emotional attachment as *affect*. We prefer the former term because the latter is often used to refer to a different concept, namely, the experience of a feeling or emotion (see Parrott 1996).

results in decreased error rates (Treatment 2 versus Treatment 3 in Charness and Levin 2005). Following dual-process theories, we postulate that by removing the win–loss feedback from the first draw, the cue on which the automatic reinforcement heuristic operates is also removed. Accordingly, there is no cue that could trigger this process in this situation, and hence in treatment NEUTRAL there is neither conflict nor alignment of decision processes.

4. Results

A simple computation reveals that the expected payoff for the two draws together is maximized by starting with a draw from right (hence learning the state of the world for sure) and then deciding accordingly for the second draw. Hence, a Bayesian optimizer should always start with the right urn if given a choice, and failing to do so is a first-draw mistake.

The most interesting mistakes, however, are those committed in second-draw decisions, which can be of two types. Errors in case of conflict arise after an initial first draw from the left urn, since the reinforcement heuristic and Bayesian updating favor different options. Errors in case of alignment arise after an initial first draw from the right urn, since the state of the world is revealed and both processes concur. Such errors should be less frequent. In treatment ALIGN, both processes are always aligned and all errors are of the second type.

4.1. Error Rates

Table 1 presents error frequencies for all treatments and (first- and) second-draw decision situations. As expected, errors in case of alignment are clearly less frequent than in case of conflict. The removal-of-valence effect is also present: error rates are significantly lower in treatment NEUTRAL than in treatment BASE (Mann–Whitney–Wilcoxon (MWW) test on individual-level error rates, $z = 3.07$, $p = 0.002$ after left win; $z = 2.71$, $p = 0.007$ after left lose). This effect is in accordance with the dual-process interpretation, since the reinforcement heuristic is not cued, and there is no decision conflict. Additionally, the low error rates in this treatment show that participants were fully capable of processing information and deciding in a Bayesian way.

Table 1 **Error Frequencies**

Treatment	Initial errors	After right win	After right lose	After left win	After left lose
BASE	15.0% (900) [2]	1.0% (612) [6]	5.1% (603) [6]	64.6% (294) [2]	63.9% (291) [2]
HALF	18.5% (840) [1]	6.9% (549) [3]	12.1% (556) [3]	55.1% (301) [1]	51.8% (274) [1]
ASYM1	25.7% (870) [3]	4.5% (650) [6]	7.2% (431) [9]	63.5% (403) [1]	48.4% (256) [1.5]
ASYM2	21.0% (900) [3]	0.9% (466) [9]	6.0% (695) [6]	56.2% (265) [1.5]	59.6% (374) [1]
ALIGN	—	14.4% (436) [2]	38.9% (404) [2]	11.4% (498) [2]	25.1% (462) [2]
NEUTRAL	—	—	—	31.0% (920) [2]	36.3% (880) [2]

Notes. The number of observations is in parentheses (n), and the error cost is given in square brackets [c]. Shaded observations correspond to situations with conflict.

Error rates did not decrease with increased incentives: individual error rates in treatments BASE and HALF did not differ (MWW, $z = 0.859$, $p = 0.391$ after left win; $z = 0.678$, $p = 0.498$ after left lose). Camerer and Hogarth (1999) report on similar instances and argue that there might be a "ceiling effect" for complex tasks. This might also explain our data, if increased incentives led to higher cognitive effort but the latter did not translate into higher performance.

Table 1 also shows the error (opportunity) costs in square brackets. The value of a black ball was set at 18 euro cents (except for treatment HALF) so that all error costs for second draws after first left draws in the experiment were either 1, 1.5, or 2 cents.[13] We compared error rates in comparable situations with identical costs (e.g., the two possible errors in case of conflict in treatment BASE, or the two pairs of errors with the same error cost in treatments ASYM1 and ASYM2) and found no significant differences (WSR and MWW tests). This is as expected, since if there is a relationship between error rates and costs, error rates in situations with the same error cost should be comparable. This is, however, by no means evidence of an inverse relationship. We will retake the discussion of the effects of monetary incentives within the regression analysis below.

4.2. Response Times

Table 2 reports the median response times conditional on correct and wrong choices for each situation. For the basic treatments where both conflict and alignment were possible (BASE, HALF, ASYM1, ASYM2) and decisions after a first draw from the left (conflict), response times for correct choices are longer, whereas the opposite is true for decisions after a first draw from the right (alignment). The latter observation also holds in treatment ALIGN, where no conflict was possible. Furthermore, decisions in case of conflict take longer than in case of alignment in the basic treatments.

If errors in case of conflict (alignment) are faster (slower), faster decisions should result in errors more often (less often). As an illustration, we classified

[13] The error costs for the first draw are computed using the expected payoff of a decision maker who chooses either left or right for the first draw, but then behaves as a Bayesian expected utility maximizer in the second. Hence they rely on a behavioral counterfactual and should not be overinterpreted.

Table 2 **Population Median Response Times (in Milliseconds) Conditional on Correct and Wrong Choices**

Treatment	Type	After right win	After right lose	After left win	After left lose
BASE	Error	2,070 (6)	1,793 (31)	1,604 (190)	1,563 (186)
	Correct	759 (606)	971 (572)	2,744 (104)	3,407 (105)
HALF	Error	1,257 (38)	1,177 (67)	1,501 (166)	1,636 (142)
	Correct	810 (511)	905 (489)	2,700 (135)	2,375 (132)
ASYM1	Error	2,514 (29)	1,865 (31)	1,343 (256)	1,278 (124)
	Correct	673 (621)	849 (400)	1,644 (147)	2,350 (132)
ASYM2	Error	4,668 (4)	785 (42)	1,238 (149)	1,620 (223)
	Correct	630 (462)	860 (653)	2,311 (116)	2,038 (151)
ALIGN	Error	1,336 (63)	917 (157)	1,098 (57)	1,090 (116)
	Correct	750 (373)	806 (247)	822 (441)	825 (346)
NEUTRAL	Error	—	—	1,797 (285)	2,488 (319)
	Correct	—	—	1,831 (635)	2,539 (561)

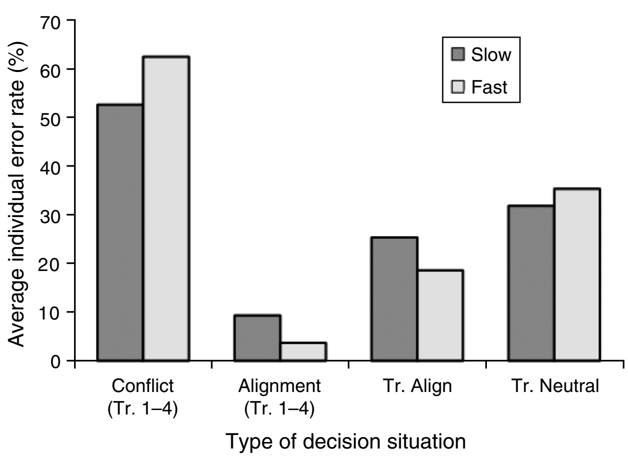
Notes. The number of observations is given in parentheses. Shaded observations correspond to situations with conflict.

each of the second-draw decisions of each participant as fast if the response time was below the participant's median, and slow otherwise. Average error rates across all participants, conditional on speed, are depicted in Figure 2, showing that errors in case of conflict were more frequent for fast decisions, but errors in case of alignment were more frequent for slow decisions.

Hypothesis 1. *In alignment situations, errors are slower.*

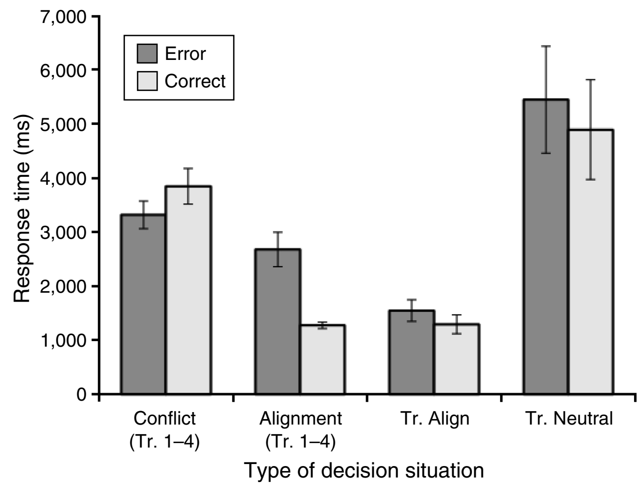
The intuition behind this hypothesis is that, in alignment situations, the automatic reinforcement process favors the correct choice, and hence most

Figure 2 **Average Individual Error Rates in the Second Draw, After a Median Split Dividing Decisions Into Fast and Slow According to the Individual Median Response Time**



Notes. Conflict (Tr. 1–4) and Alignment (Tr. 1–4) correspond to decisions in case of conflict (after a first draw from left) or alignment (after a first draw from right) for participants in the four basic treatments. Tr. Align and Tr. Neutral correspond to treatments ALIGN (where processes were always aligned) and NEUTRAL (where presumably the automatic process was shut down), respectively.

Figure 3 **Mean Individual Average Response Times for the Second Draw**



Notes. Decision situations are as in Figure 2. Error bars show one standard error from the mean.

of the errors actually come from the noisier controlled process, which is slower. To test this prediction, we computed individual average response times after first draws from the right urn, conditional on a correct or incorrect answer (see Figure 3). We then conducted two-tailed Wilcoxon signed-rank (WSR) tests for paired samples. First, we look at the four basic treatments, where both conflict and alignment were possible. Of the 57 participants who did commit some mistake after an initial right draw in these treatments, 40 exhibited slower responses in case of error. When both processes are aligned, incorrect responses are significantly slower ($z = 4.11$, $p < 0.0001$). The difference remains when splitting the test depending on whether the initial draw resulted in a win ($N = 22$, $z = 3.65$, $p = 0.0003$) or a loss ($N = 52$, $z = 3.05$, $p = 0.002$). Second, we look at treatment ALIGN, where decisions after initial draws from the left and right are equivalent and both processes are aligned. We pooled all second-draw decisions for each participant and computed individual average response times conditional on correct and incorrect responses. Incorrect decisions tend to be slower, with 18 of the 28 participants who committed errors in this treatment exhibiting slower responses in case of error (WSR test, $z = 1.64$, $p = 0.101$; two-sided t-test, $t(27) = 2.16$, $p = 0.040$).

Hypothesis 2. *In conflict situations, correct responses are slower.*

This hypothesis is intuitive, because in case of conflict, the faster reinforcement process is error prone, whereas the slower controlled process favors the correct choice. We conducted WSR tests on individual average response times after first draws from the left urn. Of the 112 participants who committed some mistake after an initial left draw in the four basic treatments, 72 exhibited quicker responses in case of errors. Average response times were significantly different ($z = -2.51$, $p = 0.012$; see Figure 3). Splitting the test depending on first-draw results, the difference is highly significant after a win ($N = 82$, $z = -3.07$, $p = 0.002$), but not after a loss ($N = 99$, $z = -1.33$, $p = 0.182$). For treatment NEUTRAL (neither conflict nor alignment), Proposition 1 makes no prediction. Following the argument of the proof, the model predicts no differences, and we indeed find no differences on average response times for correct decisions versus errors ($z = 0.706$, $p = 0.480$).

Hypothesis 3. *Situations with a decision conflict involve longer response times than alignment situations.*

This hypothesis rests on the dual-process assumption that conflict detection and resolution takes time. A WSR test compared the average response time after a first draw from either left (conflict situation) or right (alignment), separately for win and loss events. The difference is significant for wins ($N = 117$, $z = -8.827$, $p < 0.0001$) and losses ($N = 117$, $z = -8.582$, $p < 0.0001$).

Hypothesis 4. *Neutral situations involve longer response times than alignment situations.*

Recall that neutral situations are those where the win/loss cue on which the reinforcement process operates is absent, and hence only the slower controlled process can be activated. To test this hypothesis, we conducted a two-tailed MWW test for differences between average response times at the individual level in treatments ALIGN (average response time, 1.303 s) and NEUTRAL (average response time, 4.992 s). The difference is of course highly significant ($z = -5.84$, $p < 0.0001$). This is compatible with our interpretation that the removal of valence leads to the automatic, reinforcement process being unavailable. Hence the central executive always leads to processing with the more controlled, rational process that we identify with a proxy of Bayesian optimizing, which results in longer response times and also lower error rates.

We can also compare treatment NEUTRAL with treatment BASE, on which it is based. For that, and since in the former all first draws were from the left urn, we need to consider only decisions made after a first draw from the left urn. There is, however, no clear-cut prediction for response times. Controlled processes are more dominant and should hence increase response times. However, since the cues that activate the reinforcement process (payment for the first draw) are absent, the decision situations in treatment NEUTRAL correspond neither to conflict nor to alignment (they are "neutral"), hence the conflict detection phase might require less time (recall §2). In conclusion, we have no hypothesis concerning a comparison of response times between treatments BASE and NEUTRAL. We conducted two-tailed MWW tests for differences between average response times at the individual level and found no significant differences ($z = -0.399$, $p = 0.690$ after left win; $z = -0.858$, $p = 0.391$ after left lose).

4.2.1. Observation: Incentives and Response Times. A further observation concerns the incentive-motivated comparison of treatments BASE and HALF, which were identical except for the fact that the payoffs in HALF were half the ones in BASE. Higher incentives do not clearly lead to longer response times, and hence (to the extent that response times can be taken as a correlate of cognitive effort) we do not find evidence for higher incentives leading to higher effort in this framework. This was confirmed through two-tailed MWW tests for differences between response times, which were all nonsignificant (after right win, $z = -1.01$, $p = 0.312$; after right lose, $z = 0.373$, $p = 0.709$; after left win, $z = 0.187$, $p = 0.852$; after left lose, $z = 1.03$, $p = 0.304$).

4.3. Regression Analysis

Our data form a strongly balanced panel, with 60 second-draw observations per participant, and hence we can confirm the stability of our results and gain further insights by conducting appropriate regressions, which allow us, e.g., to identify treatment or incentive effects while controlling for conflict or forced decisions.

Table 3 reports a random-effects probit regression on second-draw decisions. The results are remarkably congruent with the predictions of dual-process theories. First, a dummy variable capturing the existence of a decision conflict between Bayesian updating and reinforcement has a large, highly significant

Table 3 **Random-Effects Probit Regression on Second-Draw Errors (0 = Correct, 1 = Error)**

Variable	β	SE
Conflict (1 = Yes)	1.763***	0.112
Counterbalance	−0.074	0.059
Forced (1 = Yes)	0.017	0.060
OpportunityCost	−0.057**	0.023
1*stDraw* (1 = Success)	−0.255***	0.033
Trial Number	−0.006***	0.001
*ASYM*1	0.074	0.177
*ASYM*2	−0.047	0.175
NEUTRAL	1.147***	0.194
ALIGN	0.744***	0.195
Constant	−1.278***	0.176
Log likelihood	−4,030.73	
Wald test	1,881.57***	

Note. The number of observations is 10,620 (177×60).
**Significant at the 5% level; ***significant at the 1% level.

effect; that is, errors are indeed more likely in case of conflict, i.e., when the automatic process favors the incorrect response. Second, the difference between the dummy for treatment NEUTRAL (removal of valence) and the conflict dummy is negative and highly significant ($\beta_{\text{Neutral}} - \beta_{\text{Conflict}} = -0.616$, $p < 0.001$, SE $= 0.176$), showing a positive effect on performance when the automatic reinforcement process lacks a cue on which to act (and hence we expect controlled processes to take over more often). We also confirmed these results in further regressions controlling for personal characteristics (gender, experience in statistics, monthly spending).

The regression analysis is specially interesting to study the possible effect of incentives. In §4.1 we found no support for the hypothesis that opportunity costs (as a proxy for monetary incentives) have a positive effect on performance, as evidenced by the comparison of treatments BASE and HALF. In the regression analysis, we are able to draw from the full data set and study the effect of opportunity costs in individual decisions while controlling for treatments and the presence or absence of decision conflict. We do find opportunity costs to have a significant ($p = 0.011$), positive effect on performance, although this effect seems to be small in magnitude. We might conclude that there is a basic tendency toward increased performance with increased incentives, as would be expected from the standpoint of basic economics, but the effects are too small to be consistently observed in pairwise treatment comparisons.

Other coefficients can be readily interpreted. We control for trial number and find small but highly significant learning effects, with error rates dropping slightly over time. Interestingly, a failure in the first draw (presumably resulting in negative valence) is associated with more errors once we control for treatments. Most interesting is the fact that the treatment ALIGN's dummy is significant and negative. Although this might seem surprising at first glance, one has to remember that the regression controls for the decision conflict, and in treatment ALIGN both processes were aligned; hence the treatment dummy captures the fact that the symmetry of treatment ALIGN makes decisions more difficult (in other treatments, the right urn has a trivial composition).

The regression also controls for counterbalancing, which, as expected, had no significant effect. Also, the dummies for treatments ASYM1 and ASYM2 are nonsignificant. The dummy capturing forced trials is also nonsignificant.[14]

Table 4 **Random-Effects Linear Regression on Second-Draw Response Times (Logarithmed)**

Variable	β	SE
Conflict (1 = Yes)	0.671***	0.057
Error × *Conflict*	−0.257***	0.029
Error × *Aligned*	0.138***	0.032
Counterbalance	0.003	0.028
Forced (1 = Yes)	0.200***	0.023
OpportunityCost-Log	0.030	0.036
1*stDraw* (1 = Success)	−0.197***	0.013
Log *RT* 1*stDraw*	0.259***	0.010
Trial Number	−0.014***	0.001
*ASYM*1	−0.175**	0.084
*ASYM*2	−0.158*	0.083
NEUTRAL	0.813***	0.089
ALIGN	−0.027	0.089
Constant	5.604***	0.111
R^2	0.419	
Wald test	6,525.64***	

Note. The number of observations is 10,620 (177 × 60).
*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level.

Table 4 presents the results of the linear regressions on second-draw response times. All real-valued variables are logarithmed. The regression confirms all our hypotheses simultaneously. First, we find a large, highly significant, positive effect of the conflict dummy, confirming our previous observation that decision situations where both processes deliver opposed answers are associated with longer response times (Hypothesis 3). The regression includes the interaction terms of the dummy "error" (i.e., wrong choice) with conflict and alignment, respectively. The interaction of error and conflict is highly significant and negative, i.e., errors are quicker in the case of conflict, confirming Hypothesis 2 as derived from Proposition 1. The interaction of error and alignment is highly significant and positive, i.e., errors are slower in the case of alignment, confirming Hypothesis 1, again as derived from Proposition 1. Last, the dummy for treatment NEUTRAL is significant and positive, i.e., response times in neutral situations are longer, confirming Hypothesis 4. Note that this is a stronger test than the previous pairwise comparison with alignment situations, for here the dummy captures the comparison with all other situations. In particular, the fact that neutral situations involve no decision conflict might reduce response times with respect to conflict situations by shortening the conflict detection phase. However, the regression already controls for the absence of conflict (through the conflict

[14] However, by design the dummy for forced trials might be confounded with learning effects since lower-numbered trials had forced first draws in most treatments. An additional regression where we numbered forced trials and free trials separately found that forced first-draw decisions result in more second-draw errors (all other results are unaffected). This is consistent with research in action psychology showing that if a decision is not required (e.g., forced first draws), then a decision process might not be initiated (Achtziger and Gollwitzer 2008).

dummy). The positive sign of the coefficient is consistent with the interpretation that, after the conflict-detection phase, in neutral situations most (or all) decisions are taken by controlled processes, increasing response times.

We find again significant but small learning effects, with responses becoming slightly quicker over time. Interestingly, forced first-draw decisions also resulted in longer second-draw response times, most likely because no conscious deliberation had been initiated during the first draw. A success (inducing positive valence) in the first draw resulted in shorter second-draw response times. All of these findings were confirmed controlling for first-draw decision times (one should expect response times in both draws to be positively correlated).

5. Conclusion

Real-life decisions are often made under conditions of uncertainty. Decision makers are prone to follow heuristics. We have argued that dual-process theories can clarify the interaction between the various processes underlying decision making, especially in the presence of decision feedback. We have shown that a simple formal model drawing on ideas from social and cognitive psychology is able to capture the interaction between the focus on past performance, viewed as a reinforcement-based process, and more deliberative aspects of decision making, leading to optimization based on Bayesian updating of beliefs. Our model keeps complexity to a minimum while still delivering empirically relevant predictions.

We have used an experimental binary-action belief-updating paradigm that is well-suited to the analysis of differences between conflict and alignment situations in complex decision making. The analysis of response times confirms the predictions derived from the model. Additionally, the model is also compatible with evidence from other paradigms. For instance, De Neys (2006) examines response times in a conjunction-fallacy problem and finds that correct responses take longer. This is in accordance with our model because this paradigm presents only a conflict situation, since the heuristic behind the conjunction fallacy (Tversky and Kahneman 1983) is opposed to the normative response. In contrast, our experiment generates both conflict, alignment, and neutral situations and allows to test all four predictions of the model.

Our model and data apply to a particular setting, namely, a situation in which optimal behavior can be derived from Bayes' rule, but feedback is received in a success/failure format and the win-stay, lose-shift heuristic is likely to impair performance. Hence, our conclusions should not be generalized to other settings. Taking this caveat into account, our analysis delivers specific insights with prescriptive value for managerial decision making. First and foremost, the analysis makes clear that the focus on past performance might be a key ingredient of intuitive decision making, especially when past decisions deliver a clear success/failure feedback. "Intuitive" decisions based on this principle will feel particularly natural in spite of being potentially incorrect. Raising awareness of this possibility is the first step to avoiding potentially costly mistakes. A very simple applied lesson is that, paradoxically, decision makers should question their motives whenever a decision feels intuitively correct. If they cannot offer any better justification than "it worked in the past," they should then remind themselves that successes (or failures) are above all new information, and accordingly ask themselves what those mean in terms of the underlying uncertainty, be it market conditions or employees' capabilities.

Second, it needs to be recognized that intuitive decisions might be based on cognitive shortcuts (as the case of reinforcement principles), which are often aligned with more deliberative processes. As such, they economize both decision costs and time. It is, hence, conceivable that relying on such shortcuts becomes a metarational prescription in certain environments. For instance, this will most likely be the case if time is of the essence and the costs of potential mistakes are relatively low, or if it is possible to show that the likelihood of a process conflict is particularly low for the kind of decisions considered (as is the case in our treatment ALIGN).

Third, our data also have consequences for learning and training programs. Treatment NEUTRAL shuts down the hypothesized automatic process, resulting in significantly increased accuracy rates. This treatment represents a manipulation that improves decision making by uncoupling the informational value of decision experiences from the reward. Thus, for complex decision making, better results might be obtained if learning experiences are not rewarded, which is at odds with, e.g., incentivized learning programs.

At a more general level, we view our study as an illustration of how dual-process theories might contribute to the understanding of the ways in which humans do deviate from abstract rationality, beyond the particular paradigm we have considered. It is well established that decision makers are not the ideal optimizers assumed in neoclassical economic theory. Indeed, the study of bounded rationality has long become mainstream in economics. However, rational and boundedly rational phenomena are frequently studied in isolation. On the one hand, the homo oeconomicus of traditional economic theory is free of impulsive reactions. On the other hand, the agents typical of behavioral or evolutionary game-theoretic models often follow mindless rules of behavior with little room for reflection. While both extremes can be considered useful theoretical benchmarks and both have delivered important insights, a full-fledged theory of human economic behavior might greatly benefit from a more integrative approach.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2013.1793.

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