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# HUMAN PREFERENCES AND RISKY CHOICES

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# HUMAN PREFERENCES AND RISKY CHOICES

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Image by Roger Taylor

There are different views on what preferences for risks are and whether they are indicators of stable, underlying generic cognitive systems. Preferences could be conceived as an attitude towards a set of properties of context, memory and affect - a gauge of how much uncertainty one is willing to tolerate. This special issue aims to initiate a discussion on the stability of preferences for risks - as research has shown that different decision domains, response modes, and framing facilitate preference reversals. A consistent claim from behavioural decision researchers is that, contrary to the assumptions of classical economics, preferences are not stable and inherent constructs in individuals but are modified by levels of accessibility in memory, context, decision complexity, and type of psychological processing (e.g., sampling or computational "trade-offs" in processing). For example, in a sampling-based decision-making paradigm it is argued that preferences are not essential for making risky decisions. The existing theoretical and empirical evidence reveals that human preferences are relative and unstable, undermining the predictions of normative theory. Recent theoretical accounts in psychology have expanded the debate further by offering evolutionary models of decision-making under risk. While most of the researcher has explored optimisation goals (traditionally assumed in economics), evolutionary psychology has promoted adaptation-driven processes for risky choices. Moreover, we have witnessed a renaissance of preferences as affect rather than as a construct with psycho-economical properties. Although behavioural decision research is still engaged in challenging the foundation of economic theory, at present, opinions seem less unified as to whether preferences reflect common psychological constructs.

The special issue will focus on human preferences and risky choices. Topics include:
- Normative, descriptive and experience-based decision making
- Preference reversals
- Accessibility in memory
- Context dependence
- Psychological processing:
  i) probabilities, utilities, computations and 'trade-offs'
  ii) sampling
- Affect
- Evolutionary accounts

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# Human preferences and risky choices

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There are different views on what preferences for risks are and whether they are indicators of stable, underlying generic cognitive systems. Preferences could be conceived as an attitude toward a set of properties of context, memory, and affect – a gage of how much uncertainty one is willing to tolerate. One type of computational "descriptive" integrative decision-making theories predicts specific behavioral patterns of risky preferences. An individual's risky choice among two or more options is considered, where at least one option has an uncertain outcome[1]. Choices are based on the integration of probability and utility information into expected utilities, and trade-off comparisons of computed outcomes. It is assumed that there are lawful underlying patterns of risky preferences (e.g., the shapes of loss aversion and probability-weighting functions), and that these would reflect any relevant constraints in cognitive resources. In this spirit, in this research topic, Lebière and Anderson demonstrate that their sequence-learning model, reflecting general cognitive processes in response to constraints inherent in the task environment, is superior for modeling risky choice in terms of capturing the stability that comes from previous experience. According to Luce, there are three inherently different types of people corresponding to their values of an additional utility-model parameter representing risk preference. Birnbaum demonstrates that the TAX model, in contrast to other explanations, accounts for a lack or transitivity in people's choices. Pothos and Busemeyer show that quantum-probability theory allows the modeling of decision-making phenomena (e.g., the conjunction fallacy and violations of the sure-thing principle), which go beyond classic probability theory, because of the context- and order-dependence in quantum-probability assessment. Jones and Oaksford provide evidence for a more stable pattern of preferences in transactional decision tasks than in gambles. Given that hypothetical gambles provide results that are internally inconsistent, Baron demonstrates that a monetary-difference choice task to measure risk preference is a good indicator of people's utility function for money.

Another type of theory can be considered as "non-computational." These theories argue for processing by establishing the role of "experience" in risky decision-making, proposing that choices are not based on the utilitarian integration of probability, and utility information, and trade-off comparisons of computed outcomes. However, yet (again) it is assumed that there are lawful underlying patterns of preferences, or people use specific processing and decision-making strategies. Stewart's results of model fitting show that, for simple risky choices, an additive ("non-integrative") model can completely mimic a multiplicative ("integrative") model; however, even stability of parameter values over time and across contexts in the different models does not imply correct model identification, as the parameters map onto different psychological variables. Betsch argues and provides evidence for the conceptualization of preferences as attitudes, whose stability is determined by behavior repetition and processing style. According to Hertwig and Gigerenzer, apparent inconsistencies in risky-choice behavior can be accounted for by decision-makers' application of cognitive strategies (in particular heuristics) and the interaction of these strategies with the environment. Brandstätter contends that elicitation method strongly affects people's choices; people use many strategies, one main candidate of which is the priority heuristic. Parducci demonstrates that range-frequency theory implies that judgments are not stable across contexts; as a result, the search for higher utility leads to reduced pleasure. Brown and Matthews show that, at least under certain conditions, rank-based models and range-based models are equivalent in that both can account for apparent range effects.

Yet, still other authors explore arguments for a moderation of computational and non-computational processes of decision-making by other factors. They highlight the possibility that memory or experiences of events leak into decisions even when risk information is explicitly provided. In this research topic, Kusev and van Schaik argue and provide evidence for the idea that characteristics of (a) the decision-making context and (b) content, (c) the decision-maker (including cognitive resources and motivation), and (d) presentation format of task material (for example probability format or frequency format) all influence people's psychological processing and subsequent risky choices. It follows then that stable behavioral patterns toward risk or the use of (single) psychological strategies do not exist. Chater, Johansson, and Hall also argue that people do not have risk preferences; rather, risky choices are shaped directly by past choices or explanations thereof. Any coherence between choices will be limited to those that share superficial features.

Still other researchers provide further accounts for the apparent lack of stability of preferences. In this research topic, Fox and Tannenbaum argue that because of four specific conceptual and methodological challenges there is still a lack of evidence for stable and measurable risk preferences. Aldrovandi and van Heussen argue that the lack or degree of stability of preference in decision-making can be explained by psychological phenomena of memory; various memory phenomena lead to instability of risk preferences. Based on evidence from their neuropsychological brain research, Chen, Allen, Deb, and Humphreys argue that emotions can play a necessary functional role in decision-making, but as a consequence, emotions can alter the stability of the process. According to Dickert

[1]We use the terms "decision-making" and "choice" interchangeably. We prefer "choice," as it more clearly indicates individual behavior, but we use "decision-making," "decision," or "decision-maker" when linguistically it appears more natural to do so.

and Slovic, research on mental imagery and attention as underlying processes of affective responses and other research showing individual differences as moderators of these processes help explain why people do not hold stable values for saving human lives. Vlaev shows and provides evidence for the idea that trade-off inconsistency is a ubiquitous psychophysical anomaly, in which preferences between (pairs of) options are not reliable when the options are of the same qualitative type and/or differ on a single dimension. Villejoubert and Vallée-Tourangeau argue that the perspective of distributed cognition has the potential to provide a new way of conceiving of and accounting for the role of the environment in the construction of preference; the implication is that preferences may be very different when people interact with rather than respond to the environment.

In conclusion, the contributions in this research topic offer a range of explanations for stability in risky choice. We are looking forward to further work that comparatively tests the validity of these different explanations and work that integrates approaches to provide a better account where this seems is appropriate.

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# Preferences under risk: content-dependent behavior and psychological processing

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A common view in economics and psychology is that decision agents achieve their choices and express their respective preferences by computing probabilistic properties (probabilities and money) from a decision-making context (e.g., von Neumann and Morgenstern, 1947; Tversky and Kahneman, 1992; Starmer, 2000). In this computational processing, the main psychological mechanism requires that decision agents are able to integrate economic (contextual) attributes such as money and probabilities into subjective values; in other words people are able to construct and employ psycho-economic scales. Subsequently, when making a choice, decision agents are supposed to perform tradeoffs between the computed outputs (psycho-economic variables such as expected values) and certain monetary alternatives (see Kahneman and Tversky, 1979; Tversky and Kahneman, 1992; Starmer, 2000). Despite the dominance of descriptive approach to the decision-making (e.g., Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), theorists (Hertwig et al., 2004; Stewart et al., 2006) have recently argued for somewhat different psychological processing in decision-making, without computations (integration of attributes) and tradeoffs. In particular, a non-utilitarian structure of preferences for risk is proposed. In this approach, decision-making is accounted for by experience with sequential events, simple binary comparisons (based on context and memory), and a threshold mechanism (Hertwig et al., 2004; Stewart et al., 2006). However, recent research (Kusev et al., 2009, 2011; Jones and Oaksford, 2011), in an effort to map the nature of human preferences, explored the role of decision-making content (the influence of memory in precautionary decision-making – Kusev et al., 2009, and transactional content on temporal and probabilistic discounting of costs – Jones and Oaksford, 2011). Specifically, we distinguish the influence of decision-making *content* from that of decision-making *context* (the description of risk); we see the content of decision-making as experiential (accumulative) cognitive storage system which represents (but not necessarily accurately) experienced events and their associate frequencies as these events occur over time. Accordingly, in this article we elaborate further on the interplay of decision-making context and content, as well as potential "decision" biases as a result of sequential experience in decision-making.

## THE IMPORTANCE OF DECISION CONTENT AND PSYCHOLOGICAL PROCESSING

People's behavior in the face of risk implies that they judge and weight the probability of risky events in characteristic ways that deviate from normative theory. Nonetheless, both expected utility (EUT; von Neumann and Morgenstern, 1947) and prospect theory (PT; Tversky and Kahneman, 1992) share a common representational assumption: people's risk preferences and decisions under risk and uncertainty are task-independent. In this opinion article we pursue an opposing idea that risky choices are affected by decision content, even when utilities and probabilities are known. In contrast with PT (Tversky and Kahneman, 1992) and experienced-based decision-making (e.g., Hertwig et al., 2004), we suggest that people do not have stable preferences (Kusev et al., 2009, manuscript in preparation); instead, context, accessibility to content of decision-making, task demand, and skills determine choices. Accordingly, we argue that any assumption about a particular behavioral pattern for risk as well as the assumption of a single type of processing (e.g., computational or non-computational processing in decision-making) is difficult to justify. Indeed, in decision-making, humans might be able to exhibit different patterns and use different types of processing [e.g., computing the probabilistic information from the context or sampling from memory (content of decision-making) and context].

Our position is that the particular combination of contextual factors, accessibility to content, demands, and skills trigger a particular type of processing, which then results in preferences. For example, task relevance has been demonstrated to influence processing style in risky choice. Task with high relevance result in the application of an analytic processing style, but the opposite is true for tasks with low personal relevance, leading to the application of a holistic processing style (McElroy and Seta, 2003). We speculate that some of the differences between experience-based and description-based decision-making reflect differences in psychological processing (e.g., computational and non-computational processing; holistic and analytical psychological processing). Commonly, as in learning about decisions from experience, the risky events in the real world are experienced sequentially and separated from the context provided by subsequent events in a temporally extended sequence. However, some risky events are not experienced individually over time, but are reviewed retrospectively and can also immediately be viewed holistically such that any overall pattern will be immediately apparent – as with learning about decisions from descriptions. Nevertheless, in both situations decision-makers refer to exactly the same data points in order to make their choices (or express their risky preferences). In Kusev et al. (2009), the empirical results and probability-weighting fittings indicated a failure of the descriptive invariance axiom of EUT. For risky choices, people overweighted small, medium-sized, and moderately large probabilities: respondents exaggerated risks. It was concluded, that exaggerated risk is caused by the accessibility of events in memory (content of decision-making): the weighting function varies as a function of the accessibility of events. This result suggests that people's experiences of events leak into decisions even when risk information is explicitly provided; variation in decision content produces variation in preferences for risk.

## DO EXPERIENCED SEQUENTIAL PATTERNS SHAPE PREFERENCES?

It is difficult to imagine that our experiences and associated memories do not shape our future choices. Indeed, the right question to ask is not whether this is plausible, but how and why preferences and judgments are shaped by experiences and their sequential pattern. Recent research on frequency judgments and memory (Kusev et al., 2011) demonstrates that participants do not make frequency judgments by sampling their memory for individual items; participants judged frequencies relative to experienced sequential patterns (sequentially encountered stimulus properties of the stimulus sequence configuration).

Traditionally, research in cognitive psychology has argued that decision-makers are constrained by limitations of information-processing and memory (Simon, 1956), and hence have a propensity to avoid cognitive load. We argue that this, in turn, will encourage them to respond to "appropriate processing" informed by simple patterns (Kusev et al., 2011), decision-making content, and memory (e.g., Kusev et al., 2009; Jones and Oaksford, 2011) – all psychological mechanisms that may account for people's risky decision-making. In Kusev et al. (2011) a series of experiments studied relative-frequency judgment of items drawn from two distinct categories. The experiments showed that judged frequencies of categories of sequentially encountered stimuli are affected by properties of the experienced sequences, through the first-run effect, whereby people overestimate the frequency of a given category when that category was the first *repeated* category to occur in the sequence. We also found dissociation between judgments and recall; given two types of event, respondents may judge one type more likely than the other and yet recall more instances of the latter. Specifically, the distribution of recalled items does not correspond to the frequency estimates for the event categories, indicating that participants do not make frequency judgments by sampling their memory for individual items as implied by other accounts such as the availability heuristic (Tversky and Kahneman, 1973) and the availability process model (Hastie and Park, 1986).

The first-run effect could have particularly important implications for people's decision-making under risk in situations where experienced frequency of outcomes is the only basis for assessing likelihoods (e.g., experienced-based decision-making research; Hertwig et al., 2004). However, these studies did not require people to make explicit judgments of frequency – only to make decisions where experienced frequency of outcomes was an input to a risky decision. It is therefore worth considering also asking respondents in future decision-making studies to explicitly judge the experienced frequency of types of event experienced in sequences, or to make risky decisions where the judged likelihood of the experienced events is input for those decisions. Moreover, according to the foundation of economic theory, people have stable and coherent preferences that guide their choices between alternatives varying in risk and reward. In all their variations and formulations, UT (von Neumann and Morgenstern, 1947), and PT (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) share this assumption. This view, for stable predictable patterns of preferences for risk, is shared by experience-based decision research, which reports (in contrast to PT) that probability of recently sampled information is overweighted (Hertwig et al., 2004). Nonetheless, it is possible that people simultaneously both overestimate experience-based likelihoods but also underweight their impact on risky decisions. The possibility of this sort of dissociation has yet to be systematically examined (cf. Kahneman and Lovallo, 1993).

## CONCLUSION

In conclusion, going beyond our research examples of the role of accessibility and decision-making and sequence-influenced frequency judgment, our position is as follows. Characteristics of (a) the decision-making context and (b) content (e.g., Kusev et al., 2009; Jones and Oaksford, 2011), (c) the decision-maker (including cognitive resources and motivation; see Kruglanski et al., 2007) and (d) presentation format of task material (for example probability format or frequency format; see Gigerenzer, 2002) all influence people's psychological processing and subsequent risky choices. Many studies that limitations of space prevent us from reviewing here have demonstrated the effects of these components and their interaction on decision-making (e.g., Gigerenzer, 2002) and information-processing style (e.g., McElroy and Seta, 2003). Thus, risky choice is context- and content-dependent through the influence of specific characteristics of four components in decision-making behavior and processing.

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## REFERENCES

Gigerenzer, G. (2002). *Reckoning with Risk*. London: Penguin.

Hastie, R., and Park, B. (1986). The relationship between memory and judgment depends on whether the judgment task is memory-based or on-line. *Psychol. Rev.* 93, 258–268.

Hertwig, R., Barron, G., Weber, E. U., and Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychol. Sci.* 15, 534–539.

Jones, S., and Oaksford, M. (2011). Transactional problem content in cost discounting: parallel effects for probability and delay. *J. Exp. Psychol. Learn. Mem. Cogn.* 37, 739–747.

Kahneman, D., and Lovallo, D. (1993). Timid choices and bold forecasts: a cognitive perspective on risk taking. *Manage. Sci.* 39, 17–31.

Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–291.

Kruglanski, A. W., Pierro, A., Mannetti, L., Erb, H., and Young Chun, W. (2007). On the parameters of human judgment. *Adv. Exp. Soc. Psychol.* 39, 255–303.

Kusev, P., Ayton, P., van Schaik, P., Tsaneva-Atanasova, K., Stewart, N., and Chater, N. (2011). Judgments relative to patterns: how temporal sequence patterns affect judgments and memory. *J. Exp. Psychol. Hum. Percept. Perform.* doi: 10.1037/a0025589. [Epub ahead of print].

Kusev, P., van Schaik, P., Ayton, P., Dent, J., and Chater, N. (2009). Exaggerated risk: prospect theory and probability weighting in risky choice. *J. Exp. Psychol. Learn. Mem. Cogn.* 35, 1487–1505.

McElroy, T., and Seta, J. J. (2003). Framing effects: an analytic-holistic perspective. *J. Exp. Soc. Psychol.* 39, 610–617.

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychol. Rev.* 63, 129–138.

Starmer, C. (2000). Developments in non-expected utility theory: the hunt for a descriptive theory of choice under risk. *J. Econ. Lit.* 38, 332–382.

Stewart, N., Chater, N., and Brown, G. D. A. (2006). Decision by sampling. *Cogn. Psychol.* 53, 1–26.

Tversky, A., and Kahneman, D. (1973). Availability: a heuristic for judging frequency and probability. *Cogn. Psychol.* 5, 207–232.

Tversky, A., and Kahneman, D. (1992). Advances in prospect theory: cumulative representation of uncertainty. *J. Risk Uncertain.* 5, 297–323.

von Neumann, J., and Morgenstern, O. (1947). *Theory of Games and Economic Behavior*, 2nd Edn. Princeton, NJ: Princeton University Press.

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# The non-existence of risk attitude

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Where do risk preferences come from? How do we decide if it is safe to eat unpasteurized cheese, whether to take up paragliding or mini-golf as a new hobby, whether to save in government bonds or place our money in a new technology hedge fund?

Asking about the origin of risk preference in this general form requires two presuppositions, both of which may be challenged. The first presupposition is that there is some *unitary* basis to decisions about risk, where the nature of such risks (whether food poisoning, instant death, social embarrassment, or financial disaster) may vary substantially. The second presupposition is this unitary basis determines *stable* risk preferences, which help determining our choices when faced with risk.

Regarding the first issue, Slovic (1987) has argued persuasively that there are many dimensions to the perception of risk (e.g., level of knowledge, feeling of control, novelty), and that each dimensions influences decision-making differently. Moreover, many studies have shown that the superficial characteristics of the same underlying risk (e.g., whether that risk is framed as a gamble, investment, or insurance problem) leads to wildly varying, and fairly uncorrelated, choices (Vlaev et al., 2010). Results such as these raise the possibility that the process of psychological or emotional risk-taking is divided into a multitude of different mechanisms.

Regarding the second issue, again a wide variety of studies indicate that people's risky choices are enormously flexible, not merely because of the types of framing manipulation mentioned above, but in virtue of the range of choice options presented. It is well known, for example, that people are much more likely to choose an option that is presented as a default (Johnson and Goldstein, 2003). Moreover, people's risk preferences can be radically shifted by changing the range of options available. One powerful illustration of this, prospect relativity, has been found with conventional risky gambles (Stewart et al., 2003), in which people are happy to choose, say, a low-to-middle option in a range of low-risk-low-return alternatives, while simultaneously preferring a low-to-middle option in a completely non-overlapping range of high-risk-high-return options. Thus, people will happily generate completely inconsistent choices concerning preferences of their optimal balance between risk and return, and may, indeed, give such contradictory choices within a few minutes, in a single experimental session.

One approach to these concerns is to try to build a highly multifaceted and flexible account of risk preference. We suggest pursuing an alternative strategy: to aim to explain how people make decisions, including decisions about risk, without drawing on any underlying psychological notion of risk attitude at all.

Suppose, for example, that people make decisions about whether to eat unpasteurized cheese, to paraglide, or invest in a hedge fund, simply by copying past behaviors. For example, if everybody eats unpasteurized cheese in my community, I will probably eat it too. If all my friends invest in hedge funds, it is likely that I will do it too. There has been an enormous amount of research from neuroscience to social science, and across a wide range of species, which suggests that imitative behavior is widespread across the biological and social world (e.g., Whiten et al., 2004; Boyd and Richerson, 2005; Hurley and Chater, 2005; Raafat et al., 2009).

Note too, that we also seek to copy our own past behavior. Thus, if I usually play the lottery, I will probably play it again this week; if I have skied many years, I am likely to continue. A particularly vivid illustration of the degree to which our current choices are shaped by our own previous behavior is given by the phenomenon of *choice blindness* (Johansson et al., 2005). In a typical choice blindness task, people asked to choose which of two options they prefer; they are then given what they believe to be their chosen alternative and asked to justify their selection. Crucially, on a minority of trials a conjuring trick is used to present people with the non-selected option. Typically people do not notice that they have been given the "wrong" option; moreover, they are also able to offer elaborate reasons for the choice they now believe they had made. These verbal reports have been analyzed on a number of different dimensions, such as the level of effort, emotionality, specificity, and certainty expressed, but no substantial differences between manipulated and non-manipulated reports was found (Johansson et al., 2005, 2006). The lack of differentiation between reasons given for an actual and a manipulated choice is further evidence that there may be an element of confabulation in "truthful" reporting as well. In addition to attractiveness choices for faces and abstract patterns (Johansson et al., 2008), choice blindness has been demonstrated for taste and smell (Hall et al., 2010), and even for moral judgments involving hotly debated topics in the current political debate (Hall et al., submitted).

From the point of view of the present discussion, there is also recent evidence that this type of manipulation affects people's future choices and evaluations. In a new version of the original choice blindness experiment, the participants had to choose between the same pairs of faces a second time, as well as separately rate all the faces at the end of the experiment. This procedure revealed that the manipulation induced a pronounced (but to the participants unknown) preference change, as they came to prefer the originally non-preferred face in subsequent choices, as well as rate the face they were led to believe they liked higher than the one they thought they rejected (Hall et al., in preparation). Similarly, but more dramatically, it has been shown that that choice blindness can strongly influence voting intentions just a week before a national election (Hall et al., in preparation).

Even more pertinent to the theme of this special issue is an ongoing study using false feedback in choices between probabilistic and sure outcomes (Kusev et al., in preparation), in which it was found that not only do the participants fail to notice manipulations of what level of risk they are willing to accept, but they also change their overall risk preferences for repeated choice scenarios, and in some conditions even show a complete preference reversal for the probability levels[1]. Asymmetries and preference reversals for risk has been demonstrated before (see Lichtenstein and Slovic, 1971, 2006), but this is the first time it has been shown to be a consequence of a manipulation of prior choices, thus adding to the accumulated evidence that people do in fact *not* have stable preferences for risk. If they had, it seems unlikely that they would both accept a reversal of their risky choices, and, crucially, adjust their subsequent choices in line with the manipulations made.

To the degree that our current behavior is driven by past behavior (including our verbal explanations of that behavior), whether our own or other people's, then behavior may be shaped with no direct reference to risk attitudes. Note, of course, that the determinants of our current behavior include much more than mere copying. Indeed, while it is possible that some imitative behaviors and habits may involve the replication of behavior with relatively little cognitive engagement (e.g., Dijksterhuis et al., 2000), there are also many cases were the impact of past behavior is mediated by an attempt on the part of the decision-maker to provide a coherent explanation of his or her previous choices. This will not, in general, involve mere copying; indeed, the idea that we influence ourselves through the actions we take and the choices we make has a long history in psychology, with Festinger's *cognitive dissonance* (Festinger, 1957) and Bem's (1967) *self-perception theory* as the two classic theoretical rivals vying for dominance as an explanation for the effect. But it also has some notable contemporaries, like Dan Ariely with his *coherent arbitrariness* model. Work by Ariely et al. (2003, 2006) strongly suggests that arbitrary and irrelevant factors cannot only influence participants in their assessment of the utility of different goods (such as when rumination on the digits of their social security number leads participants to create wildly different anchors for how much they are willing to pay a bottle of wine), but that these factors can be maintained through longer decision trajectories, creating a form of "coherent arbitrariness" (i.e., stable market patterns of revealed preferences; Ariely, 2008). In the words of Ariely and Norton: "These results demonstrate a kind of 'self-herding', in which people observe their past behavior, infer some amount of utility and act in accordance with the inference of utility, despite the fact that this behavior can be based not on the initial choice driven by hedonic utility but on any host of trivial situational factors that impacted the first decision" (Ariely and Norton, 2008, p.14).

From this perspective, though, to the degree that people's choices are consistent, such consistency will be enforced only where direct comparison between domains is possible. And we know from research on analogical reasoning that comparisons between domains is only possible when they are highly similar at the superficial level; "deep" links between problems with different superficial characteristics are rarely recognized (Cheng and Holyoak, 1985; Chater and Vlaev, 2011). This suggests that we might expect people to be relatively consistent with regards to whether they eat, or do not eat, different varieties of unpasteurized cheese; or whether they feel it safe to engage in different types of winter sports; but we would not expect any coherence across different risk domains. Similarly, narrowing to financial risk, we might expect people to be able to naturally relate to different types of insurance product, and hence, for example, have a general tendency to insure, or not to insure, their valuables. We would not expect people to be able to make comparisons between their insurance choices and their choices concerning whether to participate in lotteries, or to invest in hedge funds. And, indeed, behavior does seem to be entirely incoherent across different financial domains, at least in experimental contexts (Kusev et al., 2009; Vlaev et al., 2010).

To summarize, the viewpoint that we have developed here has close relationships with the idea of "constructed preferences" described by Slovic (1995), i.e., the idea that people do not necessarily choose by tapping into previously established preferences (whether preferences concerning risk, or any other dimension); but that they create their preferences, on-the-fly, during the decision-making process. The present perspective pushes this line of thinking slightly further: rather than viewing people as constructing risk preferences, we suggest that the decision-making process is best explained without making reference to risk preferences at any stage. People's risky choices are shaped directly by past choices or explanations of those choices, by themselves and others; and any coherence between choices will typically be limited to choices which share superficial features, where people can directly compare their present with their past.

[1]Kusev et al. (in preparation) also contains a series of experiments exploring other aspects of risky choice, showing that not only feedback but also context, task demands, and assimilation of perceptual information influence peoples' risky choices. The ambition of Kusev et al. (in preparation) is to create a comprehensive theory of risky choice, but in the current paper we have narrowed our focus to the role of self-feedback as a factor in the formation of preferences for risk.

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## REFERENCES

Ariely, D. (2008). *Predictably Irrational*. New York, NY: Harper Collins.

Ariely, D., Loewenstein, G., and Prelec, D. (2003). "Coherent arbitrariness": stable demand curves without stable preferences. *Q. J. Econ.* 118, 73–105.

Ariely, D., Loewenstein, G., and Prelec, D. (2006). Tom Sawyer and the construction of value. *J. Econ. Behav. Organ.* 60, 1–10.

Ariely, D., and Norton, M. I. (2008). How actions create – not just reveal – preferences. *Trends Cogn. Sci. (Regul. Ed.)* 12, 13–16.

Bem, D. J. (1967). Self-perception: an alternative interpretation of cognitive dissonance phenomena. *Psychol. Rev.* 74, 183–200.

Boyd, R., and Richerson, P. J. (2005). *The Origin and Evolution of Cultures*. New York: Oxford University Press.

Chater, N., and Vlaev, I. (2011). "The instability of value," in *Decision Making: Attention and Performance XXIII* eds M. Delgado, E. A. Phelps, and T. W. Robbins (Oxford: Oxford University Press), 81–100.

Cheng, P. W., and Holyoak, K. J. (1985). Pragmatic reasoning schemas. *Cogn. Psychol.* 17, 391–416.

Dijksterhuis, A., Bargh, J. A., and Miedema, J. (2000). "Of men and mackerels: Attention and automatic behavior," in *Subjective Experience in Social Cognition and Behavior,* eds H. Bless and J. P. Forgas (Philadelphia: Psychology Press), 36–51.

Festinger, L. (1957). *A Theory of Cognitive Dissonance*. Stanford, CA: Stanford University Press.

Hall, L., Johansson, P., Tärning, B., Sikström, S., and Deutgen, T. (2010). Magic at the marketplace: Choice blindness for the taste of jam and the smell of tea. *Cognition* 117, 54–61.

Hurley, S., and Chater, N. (eds). (2005). *Perspectives on Imitation: From Neuroscience to Social Science, 2 Volume-Set. Volume 1. Mechanisms of Imitation and Imitation in Animals. Volume 2: Imitation, Human Development and Culture*. Cambridge, MA: MIT Press.

Johansson, P., Hall, L., and Sikström, S. (2008). From change blindness to choice blindness. *Psychologia* 51, 142–155.

Johansson, P., Hall, L., Sikström, S., and Olsson, A. (2005). Failure to detect mismatches between intention and outcome in a simple decision task. *Science* 310, 116–119.

Johansson, P., Hall, L., Sikström, S., Tärning, B., and Lind, A. (2006). How something can be said about telling more than we can know: on choice blindness and introspection. *Conscious. Cogn.* 15, 673–692

Johnson, E. J., and Goldstein, D. G. (2003). Do defaults save lives? *Science* 302, 1338–1339.

Kusev, P., van Schaik, P., Ayton, P., Dent, J., and andChater, N. (2009). Exaggerated risk: prospect theory and probability weighting in risky choice. *J. Exp. Psychol. Learn. Mem. Cogn.* 35, 1487–1505.

Lichtenstein, S., and Slovic, P. (1971). Reversals of preference between bids and choices in gambling decisions. *J. Exp. Psychol.* 89, 46–55.

Lichtenstein, S., and Slovic, P. (2006). *The Construction of Preference: An overview. The Construction of Preference*. New York, NY: Cambridge University Press, 1–40.

Raafat, R., Chater, N., and Frith, C. (2009). Herding in humans. *Trends Cogn. Sci. (Regul. Ed.)* 13, 420–428.

Slovic, P. (1987). Perception of risk. *Science* 236, 280–285.

Slovic, P. (1995). The construction of preference. *Am. Psychol.* 50, 364–371.

Stewart, N., Chater, N., Stott, H. P., and Reimers, S. (2003). Prospect relativity: how choice options influence decision under risk. *J. Exp. Psychol. Gen.* 132, 23–46.

Vlaev, I., Kusev, P., Stewart, N., Aldrovandi, S., and Chater, N. (2010). Domain effects and financial risk attitudes. *Risk Anal.* 30, 1374–1386.

Whiten, A., Horner, V., Litchfield, C. A., and Marshall-Pescini, S. (2004). How do apes ape? *Learn. Behav.* 32, 36–52.

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# The elusive search for stable risk preferences

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In the early morning hours of June 20, 2011 Ryan Dunn was driving his Porsche 911 GTE up to 140 miles per hour through the Pennsylvania countryside. The car careened over a guardrail and into a wooded area, killing Dunn and a passenger in a fiery crash. A toxicology report later determined that Dunn's blood alcohol level was more than twice the legal limit. Many observers found the accident somewhat unsurprising because Dunn was best known for performing dangerous stunts in the popular *Jackass* television and movie series. As one blogger put it: "This is the type of person he was. He was a risk-taker".[1] Indeed, the headline in the Philadelphia Daily News later read: "Dunn deal: Death of a risk-taker."

The public's response to the Ryan Dunn tragedy illustrates a prevalent belief that there are consistent individual differences in not only people's risk-taking behavior but also in their underlying appetite for risk. Several industries depend on this assumption. For instance, in financial services the "suitability doctrine" legally requires financial advisors to assess their clients' risk preference before dispensing advice (Mundheim, 1965). Likewise, most social–science disciplines traditionally assume stable and measurable individual differences in risk preference. However, based on our reading of the empirical literature, the common intuition that risk preference is a stable disposition may reflect more of an attribution error than empirical fact.

## FOUR CHALLENGES TO ESTABLISHING STABLE RISK PREFERENCES

To date, most laboratory measurements of risk preference either fail to adequately predict naturalistic risk-taking or are difficult to interpret. A sparse literature in economics using choices among chance gambles has had only modest success predicting some forms of naturalistic risk-taking (e.g., Barsky et al., 1997; Pennings and Smidts, 2000; Brown et al., 2006; Jaeger et al., 2010) and there are even some published failures (Brockhaus, 1980; Dohmen et al., 2005). For instance, Dohmen et al. found that willingness to invest in a hypothetical chance lottery predicted some forms of naturalistic risk-taking, but just as often yielded null effects – and furthermore, was less predictive than a single self-reported measure of general risk-propensity. We suspect that other failed studies have landed in file drawers. Even careful attempts to measure parameters of prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), the leading behavioral model of decision under risk, have yielded disappointing results, both in terms of test–retest reliability (Zeisberger et al., 2011) and prediction of choices among laboratory-constructed investments (Erner et al., 2009).

In contrast to economic measures of risk preference, some measures devised by clinical psychologists such as the Balloon Analog Risk Task (BART) and Iowa gambling task (IGT) have had moderate success in predicting naturalistic risk-taking. For instance, the BART involves pressing a button to insert puffs of air in a visually depicted balloon; each puff adds a fixed amount of money to an account, but if the balloon explodes before the participant cashes out, she receives nothing. Risk tolerance in these tasks has successfully predicted such behaviors as drug use, unprotected sex, gambling, and stealing (e.g., Bechara et al., 2001; Lejuez et al., 2002). Although these results are encouraging, such clinical tasks are not readily decomposable into basic cognitive and economic constructs that allow for a clear interpretation of risk preference (Schonberg et al., 2011).

We suggest that the elusiveness of stable and measurable risk preferences arises from a variety of conceptual and methodological challenges, including: (1) clearly defining risk and risk-taking; (2) segregating risk preference from other contributors to risk-taking; (3) differentiating risk preference from related traits; and (4) accounting for situational influences on risk preference.

## CHALLENGE 1: DEFINING RISK AND RISK-TAKING

A first challenge in identifying stable risk preferences is that different disciplines define risk – and therefore risk-*taking* – in different ways. The economics and finance literatures usually define risk in terms of variance in the probability distribution over possible outcomes (e.g., Markowitz, 1952). Thus, for economists, risk-seeking means a preference for a higher-variance payoff, holding expected value constant. In contrast, when clinicians and laypeople identify behaviors as "risky," they invoke a broader meaning of the term. Behaviors such as drug use, drunk driving, stealing, unprotected sex, and hang gliding are often thought of as risky because such behaviors can result in loss or harm to oneself or others (e.g., Furby and Beyth-Marom, 1992). Likewise, interviews with experienced managers suggest that they also construe risk in terms of exposure to possible negative outcomes, rather than variance over outcomes or some other quantifiable construct (March and Shapira, 1987). Psychometric studies have further found that that the lay conception of riskiness encompasses a *dread* dimension characterized by lack of control or potential catastrophic consequences, and an *unknown* dimension characterized by unobservable, unknown, or delayed consequences (Slovic, 1987). We note that an advantage of the economic conception of risk is that it is simple and easy to parameterize; a disadvantage is that it does not appear to coincide with natural intuitions of most risk-takers.

## CHALLENGE 2: DISTILING RISK PREFERENCE

Even if one accepts a particular definition of risk, another challenge is distinguishing risk preference from other direct contributors to risk-taking. A person may take on more

[1] http://mydisenchantedlife.wordpress.com/2011/06/27/dunn-lived-a-risky-life/

or less risk than his underlying preference would dictate (e.g., climbing a dangerous rock face) for a number of reasons. First, risk-taking could be a side-effect of pursuing an independent goal such as social approbation (e.g., responding to peer pressure) or enhancing one's self-image (e.g., a first ascent of a new route). Second, risk *perception* may drive behavior independently of risk *preference*. For instance, a climber may simply underestimate or ignore the risk. Indeed, although studies have found substantial variation in individual risk-taking across life domains, such differences can be attributed largely to variation in the perceived risks and/or benefits of such activities (Weber et al., 2002; Hanoch et al., 2006). Third, risk-taking behavior could reflect a tendency to heavily discount future consequences that are accurately perceived (e.g., favoring the immediate pleasure of smoking over possible long-term health consequences).

### CHALLENGE 3: DIFFERENTIATING RISK PREFERENCE

Even if one distinguishes risk *preference* from other direct contributors to risk-taking, this construct must be differentiated from related traits that also predict risk-taking. One trait that has been widely linked to risky behavior is sensation-seeking, the need for "varied, novel, complex, and intense sensations and experiences, and the willingness to take physical, social, legal, and financial risks for the sake of such experiences"(Zuckerman, 2007, p. 49). As this definition makes clear, sensation-seeking involves a tolerance for risk; what is less clear is the extent that risk preferences are independent of sensation-seeking drives. A second related construct is impulsivity, marked by tendencies to engage in rash action and difficulty in inhibiting impulses – not surprisingly, these characteristics are also associated with risky behaviors (Steinberg et al., 2008). Third, appetitive and inhibitory drives (e.g., as measured by the BIS/BAS scale of Carver and White, 1994) appear to predict risk-taking (Demaree et al., 2008). To our reading of the literature, the relationships between these measures and an underlying *appetite* for risk have not yet been resolved satisfactorily. For instance, some of the aforementioned constructs may be causal antecedents to risk preference; others may moderate the relationship between risk preference and risk-taking. Furthermore, some items in these scales explicitly involve naturalistic risk-taking or risk preference (e.g., "I think I would enjoy the sensations of skiing very fast down a high mountain slope" in the sensation-seeking scale; "I am a cautious person" on the Whiteside and Lynam, 2001 impulsivity scale). Mapping out these relationships will be necessary for establishing the construct validity of any measure of risk preference.

### CHALLENGE 4: SITUATIONAL INFLUENCES ON RISK PREFERENCE

Even if risk preference can be differentiated from related traits, there may be inherent limits to the proportion of variance in naturalistic risk-taking that can be explained by such a measure. This is because a number of situational variables cause even simple economic expressions of risk preference to fluctuate.

First, risk preferences change systematically with reference points such as aspiration levels. People tend to be risk-averse for gains and risk-seeking for losses of moderate to high probability (the reverse is true for low probabilities; Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Thus, they tend to be more risk-seeking when striving to reach a goal (Larrick et al., 2009) or avoid losing money (Payne et al., 1980). Moreover, past history can influence risk-taking – for instance people tend to be more risk-seeking after experiencing gains (when gambling with "house money"; Thaler and Johnson, 1990).

Second, risk preferences vary systematically with normatively irrelevant features of the choice environment. Examples include whether options are described in terms of potential gains or losses (Tversky and Kahneman, 1986), how they are labeled (e.g., as an "insurance policy" or "gamble"; Hershey et al., 1982), how they are measured (e.g., through pricing gambles or choosing among them, Lichtenstein and Slovic, 1971; Harbaugh et al., 2010), and the nature of contrasting risks (e.g., adding a "decoy" gamble can increase the attractiveness of a dominating gamble; Huber et al., 1982).

Third, risk preferences can fluctuate systematically with the decision maker's transitory state of mind. State variables that influence risk preferences include specific emotions (e.g., anger versus fear; Lerner and Keltner, 2001), level of arousal (Mano, 1994; Knutson et al., 2008), motivational state (e.g., aspirational versus protective focus; Scholer et al., 2010), feelings of security (Levav and Argo, 2010), and momentarily-activated identities (Morris et al., 2008).

## SOME REASONS FOR OPTIMISM

Despite these substantial challenges, there are reasons to believe that researchers may establish relatively stable risk preferences – or at least reasonably good prediction of future risk-taking – in the years to come.

First, risk preferences elicited using chance gambles show systematic differences across demographic groups such as age, gender, and race (e.g., Barsky et al., 1997; Byrnes et al., 1999; Donkers et al., 2001), suggesting cultural and/or biological antecedents. Indeed, there appear to be genetic correlates of risk preference. For example, there is greater convergence in economic risk preferences among identical twins than fraternal twins raised together, accounting for roughly 20% of the variation in risk-taking behavior (Cesarini et al., 2009). Genetic markers related to dopamine and serotonin transmission have also been linked to economic and financial risk preferences in the lab, as have baseline levels of testosterone (Dreber et al., 2009; Kuhnen and Chiao, 2009; Stanton et al., 2011).

Second, state variables that influence risk preference often have stable dispositional counterparts. For instance, in addition to the finding that induced anger (fear) leads to more (less) risk-seeking, researchers have found that chronic levels of anger and fear have similar associations with risk-taking (Lerner and Keltner, 2001).

Finally, it may be that some stable individual differences are masked by their predictable interaction with situation variables. For instance, individuals with higher scores on the Cognitive Reflection Test tend to be more risk-seeking for gains and less risk-seeking for losses (Frederick, 2005). Better characterization of such interactions may improve prediction of risk-taking behavior (Figner and Weber, 2011).

## WHERE DO WE GO FROM HERE?

To our reading, the elusive search for stable risk preferences has found mixed support. On one hand, there has been modest success identifying predictable differences between individuals in risk-*taking*; on the other hand, there remain substantial theoretical challenges to establishing stable risk *preferences*. Further research should:(a) define risk in a way that is crisp yet resonates with lay intuitions, (b) distill risk preference from other contributors to risk-taking, (c) model the relationship of risk preference to related traits, and (d) account for the situational factors that cause risk preferences to fluctuate.

This theoretical work will require innovations in measurement of risk preference. Following Schonberg et al. (2011), we believe that future measurement paradigms must be: (1) predictively valid, (2) readily decomposable into basic cognitive and/or economic constructs, and (3) dynamic and affectively engaging. This work may also be supported by brain imaging and other physiological measurement methods.

This last criterion merits further comment. Perhaps clinical measures of risk preference better predict naturalistic risk-taking than economic measures because they better capture the escalating tension and exhilaration that accompany risky pursuits. Some researchers have argued that anticipatory emotions are crucial contributors to risk-taking, yet have been largely ignored by traditional decision-theoretic models (Loewenstein et al., 2001). Paradigms that capture the dynamic and affective nature of risk may improve our ability to predict risk-taking and help us understand its psychological sources.

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## REFERENCES

Barsky, R. B., Juster, F. T., Kimball, M. S., and Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: an experimental approach in the Health and Retirement Study. *Q. J. Econ.* 112, 537–579.

Bechara, A., Dolan, S., Denburg, N., Hindes, A., Anderson, S. W., and Nathan, P. E. (2001). Decision-making deficits, linked to a dysfunctional ventromedial prefrontal cortex, revealed in alcohol and stimulant abusers. *Neuropsychologia* 39, 376–389.

Brockhaus, R. H. (1980). Risk-taking propensity of entrepreneurs. *Acad. Manage. J.* 23, 509–520.

Brown, S., Farrell, L., Harris, M., and Sessions, J. (2006). Risk preference and employment contract type. *J. R. Stat. Soc. Ser. A Stat. Soc.* 169, 849–863.

Byrnes, J. P., Miller, D. C., and Schafer, W. D. (1999). Gender differences in risk-taking: a meta-analysis. *Psychol. Bull.* 125, 367–383.

Carver, C. S., and White, T. L. (1994). Behavioral inhibition, behavioral activation, and the affective responses to impending reward and punishment: the BIS/BAS scales. *J. Pers. Soc. Psychol.* 67, 319–333.

Cesarini, D., Dawes, C. T., Johannesson, M., Lichtenstein, P., and Wallace, B. (2009). Genetic variation in preferences for giving and risk-taking. *Q. J. Econ.* 124, 809–842.

Demaree, H. A., DeDonno, M. A., Burns, K. J., and Everhart, D. E. (2008). You bet: how personality differences affect risk-taking preferences. *Pers. Individ. Dif.* 44, 1484–1494.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., and Wagner, G. G. (2005). *Individual Risk Attitudes: New Evidence From a Large, Representative, Experimentally-Validated Survey*. IZA Discussion Paper, No. 1730.

Donkers, B., Melenberg, B., and Van Soest, A. (2001). Estimating risk attitudes using lotteries: a large sample approach. *J. Risk Uncertain.* 22, 165–195.

Dreber, A., Apicella, C. L., Eisenberg, D. A., Garcia, J. R., Zamore, R. S., Lum, J. K., and Campbell, B. (2009). The 7R polymorphism in the dopamine receptor D4 gene (DRD4) is associated with financial risk-taking in men. *Evol. Hum. Behav.* 30, 85–92.

Erner, C., Klos, A., and Langer, T. (2009). *Can Prospect Theory be Used to Predict Investor's Willingness to Pay?* University of Muenster, Muenster, Germany.

Figner, B., and Weber, E. U. (2011). Who takes risks when and why? Determinants of risk taking. *Curr. Dir. Psychol. Sci.* 20, 211–216.

Frederick, S. (2005). Cognitive reflection and decision making. *J. Econ. Perspect.* 19, 25–42.

Furby, L., and Beyth-Marom, R. (1992). Risk taking in adolescence: a decision-making perspective. *Dev. Rev.* 12, 1–44.

Hanoch, Y., Johnson, J. G., and Wilke, A. (2006). Domain specificity in experimental measures and participant recruitment. *Psychol. Sci.* 17, 300–304.

Harbaugh, W. T., Krause, K., and Vesterlund, L. (2010). The fourfold pattern of risk attitudes in choice and pricing tasks. *Econ. J.* 120, 595–611.

Hershey, J. C., Kunreuther, H. C., and Schoemaker, P. J. H. (1982). Sources of bias in assessment procedures for utility functions. *Manage. Sci.* 28, 936–954.

Huber, J., Payne, J. W., and Puto, C. (1982). Adding asymmetrically dominated alternatives: violations of regularity and the similarity hypothesis. *J. Consum. Res.* 9, 90–98.

Jaeger, D. A., Dohmen, T., Falk, A., Huffman, D., Sunde, U., and Bonin, H. (2010). Direct evidence on risk attitudes and migration. *Rev. Econ. Stat.* 92, 684–689.

Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decisions under risk. *Econometrica* 47, 263–291.

Knutson, B., Wimmer, G. E., Kuhnen, C. M., and Winkielman, P. (2008). Nucleus accumbens activation mediates the influence of reward cues on financial risk-taking. *Neuroreport* 19, 509–513.

Kuhnen, C. M., and Chiao, J. Y. (2009). Genetic determinants of financial risk-taking. *PLoS ONE* 4, e4362. doi: 10.1371/journal.pone.0004362

Larrick, R. P., Heath, C., and Wu, G. (2009). Goal-induced risk taking in negotiation and decision making. *Soc. Cogn.* 27, 342–364.

Lejuez, C. W., Read, J. P., Kahler, C. W., Richards, J. B., Ramsey, S. E., Stuart, G. L., Strong, D. R., and Brown, R. A. (2002). Evaluation of a behavioral measure of risk-taking: the balloon analogue risk task (BART). *J. Exp. Psychol. Appl.* 8, 75–84.

Lerner, J. S., and Keltner, D. (2001). Fear, anger, and risk. *J. Pers. Soc. Psychol.* 81, 146–159.

Levav, J., and Argo, J. (2010). Physical contact and financial risk-taking. *Psychol. Sci.* 21, 804–810.

Lichtenstein, S., and Slovic, P. (1971). Reversals of preference between bids and choices in gambling decisions. *J. Exp. Psychol.* 89, 46–55.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., and Welch, N. (2001). Risk as feelings. *Psychol. Bull.* 127, 267–286.

Mano, H. (1994). Risk-taking, framing effects, and affect. *Organ. Behav. Hum. Decis. Process.* 57, 38–58.

March, J. G., and Shapira, Z. (1987). Managerial perspectives on risk and risk-taking. *Manage. Sci.* 33, 11, 1404–1418.

Markowitz, H. (1952). Portfolio selection. *J. Finance* 7, 77–91.

Morris, M. W., Carranza, E., and Fox, C. R. (2008). Mistaken identity: activating conservative political identities induces "conservative" financial decisions. *Psychol. Sci.* 19, 1154–1160.

Mundheim, R. H. (1965). Professional responsibilities of broker-dealers: the suitability doctrine. *Duke Law J.* 3, 445–480.

Payne, J., Laughunn, D., and Crum, R. (1980). Translation of gambles and aspiration level effects in risky choice behavior. *Manage. Sci.* 26, 1039–1060.

Pennings, J. M. E., and Smidts, A. (2000). Assessing the construct validity of risk attitude. *Manage. Sci.* 46, 10, 1337–1348.

Scholer, A., Zou, X., Fujita, K., Stroessner, S. J., and Higgins, E. T. (2010). When risk seeking becomes a motivational necessity. *J. Pers. Soc. Psychol.* 99, 215–231.

Schonberg, T., Fox, C. R., and Poldrack, R. A. (2011). Mind the gap: bridging economic and naturalistic risk-taking with cognitive neuroscience. *Trends Cogn. Sci. (Regul. Ed.)* 15, 11–19.

Slovic, P. (1987). Perception of risk. *Science* 236, 280–285.

Stanton, S. J., Mullette-Gillman, A. M., McLaurin, R. E., Kuhn, C. M., LaBar, K. S., Platt, M. L., and Huettel, S. A. (2011). Low- and high-testosterone individual exhibit decreased aversion to economic risk. *Psychol. Sci.* 22, 447–453.

Steinberg, L., Albert, D., Cauffman, E., Banich, M., Graham, S., and Woolard, J. (2008). Age differences in sensation-seeking and impulsivity as indexed by behavior and self-report: evidence for a dual systems model. *Dev. Psychol.* 44, 1764–1778.

Thaler, R. H., and Johnson, E. J. (1990). Gambling with the house money and trying to break even: the effects of prior outcomes on risky choice. *Manage. Sci.* 36, 643–660.

Tversky, A., and Kahneman, D. (1986). Rational choice and the framing of decisions. *J. Bus.* 59, 251–278.

Tversky, A., and Kahneman, D. (1992). Advances in prospect theory: cumulative representation of uncertainty. *J. Risk Uncertain.* 5, 297–323.

Weber, E. U., Blais, A. R., and Betz, N. E. (2002). A domain-specific risk-attitude scale: measuring risk perceptions and risk behaviors. *J. Behav. Decis. Mak.* 15, 263–290.

Whiteside, S. P., and Lynam, D. R. (2001). The five factor model and impulsivity: using a structural model of personality to understand impulsivity. *Pers. Individ. Dif.* 30, 669–689.

Zeisberger, S., Vrecko, D., and Langer, T. (2011). Measuring the time stability of prospect theory preferences. *Theory Decis.* doi: 10.1007/s11238-010-9234-3.

Zuckerman, M. (2007). *Sensation-Seeking and Risk*. Washington, DC: American Psychological Association.

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# Inconsistency in risk preferences: a psychophysical anomaly

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There is a fundamental problem with the conceptualization of the individual agent in economics and public policy. At the heart of both domains is the notion that people should be able to make stable tradeoffs between different goods and quantities. For example, people might have to choose between the benefit gained investing money in a pension fund or in joining a gym to improve their health; or they may need to trade-off risk and return when choosing a pension fund. Should policy makers help people make the right choices when faced with such difficult decisions? More pertinently, policy makers themselves frequently need to arbitrate between dissimilar options. For example, a minister may be forced to decide to fund hospitals rather than schools, and in doing so trade-off the health and education level of the population. Recent theoretical and empirical work suggests, however, that people cannot make stable tradeoffs, i.e., independent of other available choice options or the context. This inability seems to reflect a basic property of human cognition that applies right across psychology, from the basic psychophysics of sound perception right through to high-level cognitive processes in judgment and decision making.

This cognitive limitation has implications for economics and public policy where it raises important questions for the central methodologies used to measure and derive human preferences. Popular methods like functional measurement (Anderson and Zalinski, 1988) and conjoint analysis (Louviere, 1988; Green and Srinivasan, 1990) measure tradeoffs by asking respondents for attractiveness ratings of options (e.g., policies) consisting of pairs of attributes (e.g., a reduction of $x$% in the annual risk of death for £$y$). Ratings of this sort are useful if the tradeoffs are independent of other available options (e.g., "rationally irrelevant" factors like the range of values on each attribute). If a change from 30 to 60 min is worth a change from £10 to £20, then this should be true regardless of whether the range of available monetary options is from £10 to £20 or from £1 to £200. Utility of each option should depend on its consequences, not on what other options are considered; yet, such independence is often not found (Baron, 1997).

## ANOMALIES IN PSYCHOPHYSICS, CHOICE, AND VALUATION

Preferences between pairs of options may often be reliable when the options are of the same qualitative type and/or differ on a single dimension. But interesting choices tend to be more challenging in two ways: they typically involve trading off between different dimensions and comparing qualitatively different types of outcome, which is difficult even on a single dimension (such as when "comparing apples and oranges"). This article focuses on explaining one prominent psychological anomaly, *trade-off inconsistency* (TI), which violates the independence assumption of neoclassical economics. To illustrate TI, note that a person may easily judge that eating marginally more calories is preferable to eating slightly fewer; and marginally less risk of diabetes is preferable to more. But deciding what to eat involves trading off between these, and other dimensions against factors such as the pleasure obtained from food; and people appear systematically inconsistent in making such tradeoffs.

The basic underpinnings of this cognitive limitation can be found in psychophysics. Psychophysical results indicate that people do not have access to mental representations of "absolute" magnitudes, at least for perceptual stimuli; and hence base their decisions on relative, not absolute, values. For example, Garner (1954) asked people to choose a tone half-as-loud as a comparison tone. However, one group of people received candidate tones that included the half-as-loud tone but were mostly quiet, while another group received tones that also included half-as-loud tone but were mostly loud. In both groups, the recipients selected a tone in the middle of the range, so that the "quiet" group's estimates of the half-loudness were much lower than the "loud" group. The conclusion was that people have no grasp on absolute loudness; instead, they are more influenced by the alternative choice options and scarcely at all by the comparison stimulus.

Inspired by Garner's (1954) study and similar studies in psychophysics where it was shown that people have no grasp on absolute loudness (Laming, 1997), Stewart et al. (2003) showed that such psychophysical principles carry over to risky choice, where the option set (i.e., the context) affects peoples' choices, because there is no fixed internal scale according to which people make their judgments of the values of certain options. In particular, when participants choose to trade-off risk and monetary return by choosing a gamble ("$p$ chance of $x$") from a varying range of options/gambles, the range (full range of options, only safe options, and only risky options) was found to almost completely determine the choice: people chose based not on absolute risk–return level, but on the risk–return level relative to the other available gambles. In parallel work on risky financial decisions, Vlaev et al. (2007a,b) found similar effects of skew and range, in line with the range–frequency theory of magnitude judgment (Parducci, 1965, 1995). In particular, the range of options offered as potential saving levels and investment risks largely influenced the selected options, and the rank of riskiness of the investments affected the preferences for risky investment such that options with higher rank were considered as more risky and unattractive. Vlaev and Chater (2006, 2007) report similar relativistic effects in strategic decision making, where people do not have absolute grip of the level of cooperativeness implicit in each social dilemma game and, instead, such games are assessed, and strategic choices are made, relative to the range, rank, or mean cooperativeness of previous games that have been encountered. Such relativistic responses are inconsistent with an absolute measure of utility, or related concepts such as the value-function in prospect theory (Kahneman and Tversky,

1979) and rank-dependent utility (Quiggin, 1993), because these TIs cause preference reversals, which cannot be explained by classical, reference-, or rank-dependent utility models.

These results are related to other studies of context effects. Baron (1997) presents evidence that people judge the utility of a change or a difference as a proportion of the overall magnitude, even when the change alone is more closely related to their goal; and as a result, judgments are dependent on the maximum magnitude on each attribute scale. Another classic example is the jacket-calculator problem of Tversky and Kahneman (1981, p. 457; replicated by Darke and Freedman, 1993), which asks people to make a hypothetical choice between a jacket for $125 and a calculator for $15. When respondents were informed that the calculator is on sale for $10 at another store located 20 min away, most of them preferred the trip to save the $5, but only few respondents in another condition selected to make the trip to save $5 on the jacket, although the real trade-off is about whether one would be willing to drive 20 min for $5. Therefore, people judge the utility of saving $5 as a proportion of the specific money attribute, not on the basis of a trade-off between money and time (opportunity cost); which goes against normative choice models such as multi-attribute utility theory (Keeney and Raiffa, 1976). Similar context effects are caused by relative reference points in studies of perception of economic attributes such as price (Niedrich et al., 2001).

Vlaev et al. (2009) demonstrate TI in an incentivized auction experiment (Becker-DeGroot-Marshack, 1964), in which participants choose to pay to avoid painful electrical shocks. These valuations were determined by two factors: recent intensities of other pains – medium pain provoked markedly higher price offers when it occurred with low pain rather than high pain; and immediately disposable income – higher offers were made when the endowment-per-trial was higher (i.e. individual 'overall wealth', which should not be affected by the small variations in the endowments per trial, was not an important factor) (see **Figure 1**). The estimated consumer-demand curves for pain relief, which indicate the quantity of pain relief expected to be bought at different prices, also exhibited relativistic patterns – higher demand for relief from medium pain when paired with low rather than high pain. This suggests that the subjective value attributed to pain relief is remarkably malleable and people cannot establish a stable trade-off between money and pain (note that stable trade-off is assumed in economic valuation of pain, which informs the market price of analgesics, the cost-effectiveness of clinical treatments, compensation for injury, and the response to public hazards). Ariely et al. (2003) demonstrated similar reference-dependence of preferences by showing that willingness-to-pay to avoid aversive stimuli is strongly biased toward arbitrary price anchors.

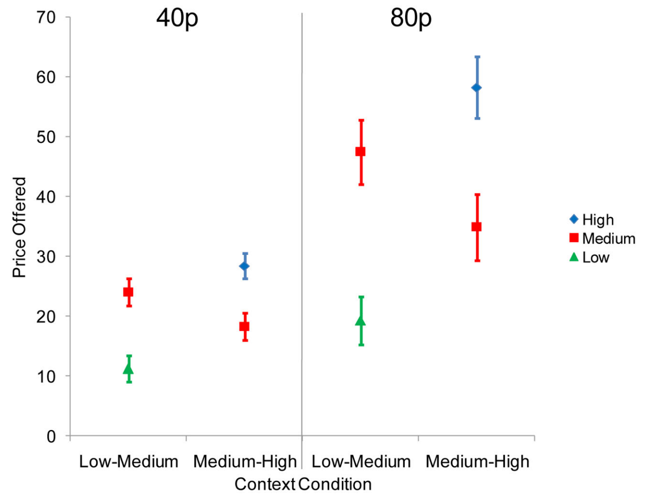


**FIGURE 1 | Mean price offers (in pence) for the three pain levels, depending on endowment and context pairing (Vlaev et al., 2009).** Error bars indicate standard errors of the mean. The medium pain provoked markedly higher price offers when it occurred with low pain in both 40 pence and 80 pence endowments. All pain levels received higher offers when the endowment per trial was 80 pence.

Another type of TI is due to variation in decision "content" (different from "context" or the choice set), which produces variation in preferences for risk, because people's knowledge of event frequencies "leaks" into decisions even when event likelihood information is explicitly provided (Kusev et al., 2009).

In summary, the fact that individuals are subject to contextual biases, and as a result behave inconsistently, is important. From this basis, this article aims to offer an explanatory account of such TI effects.

## COMMENSURABILITY EXPLAINS INCONSISTENT DECISION MAKING

Trade-off inconsistency are not cognitive oddities – they arise systematically from basic properties of the cognitive system. A fundamental cognitive principle, which promises to explain the above phenomena, is *qualitative incommensurability* (QI). This principle postulates that people are unable to systematically compare qualitatively different options or outcomes on a single value dimension – an assertion based on existing evidence that such comparisons are extremely difficult (Luce and Green, 1978; Stewart and Chater, 2003). Recent psychophysical research has suggested that basic judgments of perceptual quantities like loudness, qualitatively different stimuli cannot be consistently compared, *even when judged on the same attribute*, and judgments are distorted by the influence of previous context. Stewart and Chater (2003) presented participants with two different auditory stimuli, either pure tones or white noise ("buzzes") delivered independently via headphones to each ear, and the task was to choose the loudest tone. The loudness of previous items strongly influenced the perceived loudness of the present item, but this effect was reduced when items were qualitatively different – a previous loud "tone" made a present "tone" quieter, but not a present "buzz," thus modifying the choice between them. Where this phenomenon occurs in relation to choices that are presumed to reveal preference (e.g., choice between using money to preserve a 80 acres of marshland vs. providing clean drinking water for 2000 people), we face a substantial puzzle, because preference reversals will be generated by varying the previous items (e.g., saving 180 acres of marshland vs.

clean drinking water for 1000 people). But then which choice reveals a person's "true" preference? There is no "neutral" context in which psychophysical, or other, judgments are made. Hence, this result raises concerns over the extent to which contextual effects undermine our ability to stably trade-off between qualitatively different goods.

Stewart and Chater's (2003) results in "perceptual choice" (see also Luce and Green, 1978) imply that even apparently similar dimensions (loudness of sounds) may not be commensurable. Psychophysical research also reveals that the decision context determining choice is often the immediately preceding stimuli, as in the related domain of absolute magnitude identification (Stewart et al., 2005).

In "preferential choice," most interesting decisions also involve comparing incommensurable properties – e.g., dietary restraint against risk of heart disease, mobility maintenance in patients against pain avoidance, financial vs. environmental factors, investment risk vs. return. Consider a person on a diet who may find it difficult to assess the pleasure they may get from either of two 100 calorie treats: a thin sliver of cake, or 10 grapes; likewise, a typical public policy budgeting decision involve relating qualitatively different outcomes, such as heart transplants, educational programs, or air quality improvements, against a fixed overall budget. These choices are difficult in part due to a lack of information (e.g., about how health behaviors relate to levels of health risk; or in public policy, the amount of marginal health, educational, or environmental benefit per pound spent). QI implies that the problem is more fundamental – even with perfect information, basic properties of the cognitive system appear to show that such preferences are undefined.

In contrast, normative theories and their descriptive deviations assume that an attribute's value is "translated" into a single underlying measure called "utility," which can be positive or negative; and after all attributes are independently "mapped" on this "common currency" scale, the overall utility of an option is determined by some additive process. To illustrate this point, imagine that a person is indifferent between eating an apple and two oranges, and she tries another extremely delicious fruit. Normative decision theories predict that this new experience should not affect her initial trade-off (e.g., by making her demand two apples for two oranges). Reference-dependent utility theories predict that the pleasure from these apples and oranges should be reduced, while the trade-off is preserved, which happens irrespective of whether she tries a delicious apple, orange, or any other fruit; because, the greater new utility affects all smaller utilities by changing their reference points (i.e., the pleasure from eating apples is not calculated on a separate utility scale). QI predicts that the trade-off is likely to vary depending on the commensurability between two options, and thus can differentially undermine the quality of choice. Therefore, the cases in which QI is strong enough to lead to context effects and preference reversals are the most intriguing.

To summarize, QI is a prominent psychological anomaly that has implications for explaining TI in choice and valuation across decision domains like health, the environment, finance, and consumer-spending. There are also crucial implications for normative theories of rational choice, consumer-theory (e.g., calculating a "commensurability index" between products before deriving their indifference curves), and the practical methodology of valuing non-market goods.

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## REFERENCES

Anderson, N. H., and Zalinski, J. (1988). Functional measurement approach to self-estimation in multiattribute evaluation. *J. Behav. Decis. Mak.* 1, 191–221.

Ariely, D., Loewenstein, G., and Prelec, D. (2003). Coherent arbitrariness: stable demand curves without stable preferences. *Q. J. Econ.* 118, 73–105.

Baron, J. (1997). Biases in the quantitative measurement of values for public decisions. *Psychol. Bull.* 122, 72–88.

Becker, G. M., DeGroot, M. H., and Marschak, J. (1964). Measuring utility by a single-response sequential method. *Behav. Sci.* 9, 226–232.

Darke, P. R., and Freedman, J. L. (1993). Deciding whether to seek a bargain: effects of both amount and percentage off. *J. Appl. Psychol.* 78, 960–965.

Garner, W. R. (1954). Context effects and the validity of loudness scales. *J. Exp. Psychol.* 48, 218–224.

Green, P. E., and Srinivasan, V. (1990). Conjoint analysis in marketing: new developments with implications for research and practice. *J. Mark.* 45, 33–41.

Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–291.

Keeney, R. L., and Raiffa, H. (1976). *Decisions With Multiple Objectives: Performances and Value Trade-Offs.* New York: Wiley.

Kusev, P., van Schaik, P., Ayton, P., Dent, J., and Chater, N. (2009). Exaggerated risk: prospect theory and probability weighting in risky choice. *J. Exp. Psychol. Learn. Mem. Cogn.* 35, 1487–1505.

Laming, D. (1997). The Measurement of Sensation. Oxford: Oxford University Press.

Louviere, J. J. (1988). *Analyzing Individual Decision Making: Metric Conjoint Analysis.* Newbury Park, CA: Sage.

Luce, R. D., and Green, D. M. (1978). Two tests of a neural attention hypothesis for auditory psychophysics. *Percept. Psychophys.* 23, 363–371.

Niedrich, R. W., Sharma, S., and Wedell, D. H. (2001). Reference price and price perceptions: a comparison of alternative models. *J. Consum. Res.* 28, 339–354.

Parducci, A. (1965). Category judgment: a range-frequency theory. *Psychol. Rev.* 72, 407–418.

Parducci, A. (1995). *Happiness, Pleasure, and Judgment: The Contextual Theory and its Applications.* Mahwah, NJ: Erlbaum.

Quiggin, J. (1993). *Generalized Expected Utility Theory: The Rank-Dependent Model.* Boston: Kluwer Academic.

Stewart, N., Brown, G. D. A., and Chater, N. (2005). Absolute identification by relative judgment. *Psychol. Rev.* 112, 881–911.

Stewart, N., and Chater, N. (2003). "No unified scales for perceptual magnitudes: evidence from loudness," in *Proceedings of the Twenty-Fifth Annual Conference of the Cognitive Science Society*, eds R. Alterman and D. Kirsh (Boston, MA: Cognitive Science Society), 1116–1121.

Stewart, N., Chater, N., Stott, H. P., and Reimers, S. (2003). Prospect relativity: how choice options influence decision under risk. *J. Exp. Psychol. Gen.* 132, 23–46.

Tversky, A., and Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science* 211, 453–458.

Vlaev, I., and Chater, N. (2006). Game relativity: how context influences strategic decision making. *J. Exp. Psychol. Learn. Mem. Cogn.* 32, 131–149.

Vlaev, I., and Chater, N. (2007). Context effects in games: local versus global sequential effects on choice in the prisoner's dilemma game. *Judgm. Decis. Mak.* 2, 380–389.

Vlaev, I., Chater, N., and Stewart, N. (2007a). Financial prospect relativity: context effects in financial decision making under risk. *J. Behav. Decis. Mak.* 20, 273–304.

Vlaev, I., Chater, N., and Stewart, N. (2007b). Relativistic financial decisions: context effects on retirement saving and investment risk preferences. *Judgm. Decis. Mak.* 2, 292–311.

Vlaev, I., Seymour, B., Dolan, R., and Chater, N. (2009). The price of pain and the value of suffering. *Psychol. Sci.* 20, 309–317.

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# Preferences show greater stability for transactions than for gambles in cost discounting

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Many factors point to the underlying instability of preferences in choice behavior. In particular, *discounting* reveals some effects not consistent with stable preferences. In discounting, the subjective value of a reward reduces as the uncertainty of or delay to obtaining it increases. The function relating subjective value to delay or probability must be exponential with a constant discount rate to respect transitivity over time, i.e., if A > B and B > C, then A > C (" > " = is preferred to). If the discount rate varies with value or time, then it is possible for transitivity to be violated, i.e., for preferences to be unstable. And people do show unstable, preference reversals over time in intertemporal choice more consistent with a hyperbolic discounting function (e.g., Myerson and Green, 1995). Thus, while someone may prefer £100 for certain now rather than £110 tomorrow, they will prefer £110 in a year and a day over £100 in a year's time. People discount rate is very high initially, more rapid than the exponential, but over time it decreases leading to a flatter function than the exponential. Consequently, the £10 difference is almost totally discounted in the short term, but in a year's time the extra day barely reduces the subjective value we attach to gaining an extra £10.

Further effects are inconsistent with the reasonable assumption that delay works by increasing uncertainty. For example, the magnitude of a reward seems to have opposite effects for uncertainty and delay. Amount has opposite effects on the discounting of delayed and probabilistic rewards (Green et al., 1999). So, in temporal discounting people seem to discount small amounts more than large amounts, e.g., they prefer £10 now to £20 in a year but prefer £200 in a year to £100 now. However, in probabilistic discounting people seem to discount large amounts more than small amounts, e.g., they prefer £20 with a 50% chance to £10 for certain but prefer £100 for certain rather than £200 with a 50% chance. This picture is further complicated by the fact that for discounting losses, there seems to be no effect of amount for temporal discounting and inconsistent effects for probabilistic discounting (e.g., Mitchell and Wilson, 2010). These effects of amount not only violate the axioms of expected utility theory but are also not consistent with descriptive decision theories such as prospect theory.

Jones and Oaksford (2011) observed that most of these results were obtained using *gambles*, whereas most people rarely receive a gain or incur a loss outside the context of a *transaction,* e.g., a choice of paying £10 now to *own a commodity now* or of paying £20 in 6 months time *to own the commodity now*. Kusev et al. (2009) showed that *precautionary decision* content, as in insurance situations, altered people's choice behavior consistent with an increase in the probability weighting function for low probability events in prospect theory. Similarly, Jones and Oaksford (2011) argued that using transactional problem content rather than gambles may alter people's decision-making. In particular, they suggested that this content may reveal more consistent effects of amount across temporal and probabilistic discounting.

Transactions – but not gambles – will bring to mind previous instances of purchasing different commodities for different amounts. In particular, people would also be expected to have access to a commodity's rate of depreciation or appreciation and they would know that the more expensive a commodity, the lower its depreciation is expected to be. Indeed, for some of their most costly purchases, people have the reasonable expectation of long-run appreciation. This information implies that in a transaction, people may discount small costs more than larger costs. So they will prefer to pay £100 now for the weekly shop rather than £200 in a week because its subjective value in a week's time will be far less than £100 if not zero. In contrast, they may well be happy to pay £200K for a new flat in 10 years rather than £100K now. The flat is likely to be worth more than £100K in 10 years, and so, over time, its subjective value is not likely to decrease much. Jones and Oaksford (2011) also made the same prediction, more discounting for small costs than larger costs, for probabilistic discounting with transactional content.

They report four experiments testing the predicted effects of transactional content on cost discounting. All these experiments used the standard adaptive staircase method to zero in on people's certainty equivalent values for three amounts given different delays and probabilities. Temporal and probabilistic discounting curves were generated by plotting the certainty equivalent value normalized by cost amount against delay or odds against loss respectively for each amount. The area under the discounting curves (AUC) was used as the dependent variable indicating the degree of discounting: the lower the area under the curve the higher the rate of discounting. **Figure 1**, Panel A shows the mean AUC values using transactional content for both delay and probabilistic discounting in Jones and Oaksford's (2011) Experiment 3, which was a replication of their Experiment 1. Both experiments showed the same pattern of discounting small costs more than large costs, i.e., lower mean AUC values for lower amounts. The trends were significant in all cases and in the same direction for both temporal (delay) and probabilistic discounting. **Figure 1**, Panel B shows the mean AUC values for their Experiment 4, which used gambles rather than transactions. For delay discounting, this experiment replicated previous findings of no effect for discounting losses. For probabilistic discounting of losses, a similar effect of more discounting for smaller amounts was observed. Moreover, for both the temporal

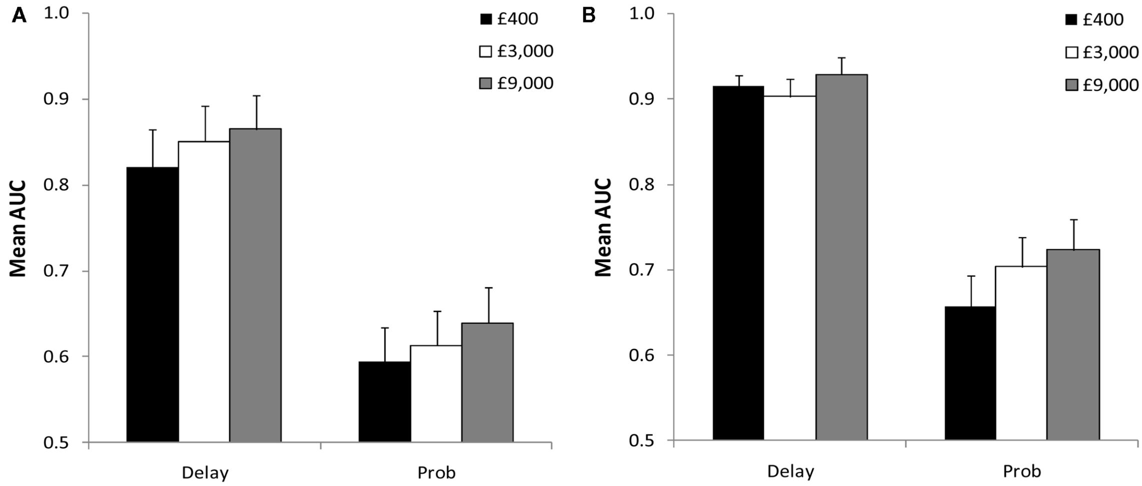


**FIGURE 1 | Mean AUC values at different levels of cost amount using transactions (A) and gambles (B) taken from Jones and Oaksford's (2011) Experiments 3 and 4 respectively.** Error bars represent SE. AUC, area under the curve; Prob, probability.

and probabilistic case, people discounted more (lower AUC values) for transactions than for gambles.

Like precautionary decisions (Kusev et al., 2009), transactions cannot be treated like pure gambles. A cost is not a pure loss because in a transaction there is always a linked gain associated with the purchased commodity. For delay discounting these differences result in a magnitude effect for transactions (Panel A) not observed for gambles (Panel B). Moreover, for transactions this effect is paralleled for probabilistic discounting of costs (Panel A). This is the first time that such parallel effects of amount have been observed for probabilistic and delay discounting. However, for probabilistic discounting, this effect was also observed for gambles (Panel B). A possible explanation is that gambles are described by *prospects*, which, like transactions, emphasize an implicit linked gain.

There are some outstanding problems. For example, for probabilistic discounting with gambles, why are smaller losses discounted more than larger losses but larger gains discounted more than smaller gains? Jones and Oaksford (2011) proposed the following possible explanation. Green et al. (1999) and Prelec and Loewenstein (1991) argued that in probabilistic discounting, gains implicitly involve corresponding losses (i.e., the possibility of wining nothing). They argued that the negative value attached to the possible loss increases faster than the positive value associated with the gain as the gain amount increases. By parity of reasoning, one could argue that losses implicitly involve corresponding gains (i.e., the possibility of losing nothing). This line of reasoning suggests that the positive value attached to the possible gain increases faster than the negative value associated with the loss as the loss amount increases. In both cases, the implicit gain or loss associated with the possibility of no change in one's financial position increases in subjective value, positive or negative, faster with amount than the subjective values attached to the possibility corresponding to an actual loss or gain. Such an account could explain the peanuts effect for probabilistic gains (overall subjective value will decrease with amount) and a magnitude effect for probabilistic losses (overall subjective value will increase with amount).

Such an account is not consistent with prospect theory, in which losses loom larger than gains. So, such an explanation works for probabilistic gains, but explaining the reverse effect for losses would seem to require gains to loom larger than losses. Of course, how *implicit* losses and gains behave when the focus of attention is on the corresponding gains and losses has not been explored. Consequently, much further work needs to be done before a complete account of the effects of amount on intertemporal choice, using transactions or gambles is forthcoming. How consistent such an account is with current descriptive decision theory or with standard discounted utility models remains uncertain.

Nonetheless, Jones and Oaksford's (2011) results show that transactions make transparent a factor, the differential depreciation of high and low value items, that reveals a more stable pattern of preferences in people's discounting behavior at least with respect to variation in cost amount. Consistent with standard discounted utility models, these results are consistent with the view that time or delay affects decision-making by increasing uncertainty. Moreover, it is arguable that people's behavior with transactional problem content is the general case and consequently how they behave with this kind of content more indicative of the rationality, or not, of their behavior in the real world. A similar trend to seeing more of people's decision-making behavior as rational or least conforming to the dictates of standard expected utility theory emerges in Regenwetter et al. (2011). They point out that it is actually quite difficult to establish inconsistency of variable choice behavior with deterministic axioms like transitivity in expected utility theory. They use the example of a student observing their supervisor's behavior when choosing between three on campus locations to meet. Choice proportions seem to reveal underlying intransitivity of choice until Regenwetter et al. (2011) reveal that the supervisor's choice of location to meet is based on how close it is to where she is teaching that day. That is, there is an underlying consistent basis for the choice although the revealed preferences seem intransitive. That is, the revealed preferences seem unstable although the latent preferences are stable.

In sum, there is emerging evidence that people's choice behavior may be less irrational or inconsistent with expected utility theory and discounted utility models than first thought. People's preferences are more stable for transactions than for gambles. Our research on transactions in cost discounting makes a small contribution to this literature that suggests exploring more fully the effects of transactions on discounting behavior when participants are asked to act as sellers as well as buyers, and when, as in real world transactions, payment and receipt of goods can vary more widely.

## REFERENCES


Green, L., Myerson, J., and Ostaszewski, P. (1999). Amount of reward has opposite effects on the discounting of delayed and probabilistic outcomes. *J. Exp. Psychol. Learn. Mem. Cogn.* 25, 418–427.

Jones, S., and Oaksford, M. (2011). Transactional problem content in cost discounting: parallel effects for probability and delay. *J. Exp. Psychol. Learn. Mem. Cogn.* 37, 739–747.

Kusev, P., van Schaik, P., Ayton, P., Dent, J., and Chater, N. (2009). Exaggerated risk: prospect theory and probability weighting in risky choice. *J. Exp. Psychol. Learn. Mem. Cogn.* 35, 1487–1505.

Mitchell, S. H., and Wilson, V. B. (2010). The subjective value of delayed and probabilistic outcomes: outcome size matters for gains but not for losses. *Behav. Process.* 83, 36–40.

Myerson, J., and Green, L. (1995). Discounting of delayed rewards: models of individual choice. *J. Exp. Anal. Behav.* 64, 263–276.

Prelec, D., and Loewenstein, G. (1991). Decision making over time and under uncertainty: a common approach. *Manage. Sci.* 37, 770–786.

Regenwetter, M., Dana, J., and Davis-Stober, C. P. (2011). Transitivity of preferences. *Psychol. Rev.* 118, 42–56.



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# Behavioral inconsistencies do not imply inconsistent strategies

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We have been here before. In psychology and philosophy, character traits have been invoked time and again to argue that people should be disposed to behave consistently across a wide range of trait-relevant scenarios. Take moral behavior. In frameworks ranging from Aristotelian moral psychology, virtue ethics, and Kohlberg's (1984) developmental stage theory of moral reasoning to contemporary economic theories of fairness (e.g., Fehr and Schmidt, 1999), the same premise applies: The virtues, traits, and social preferences a person possesses and the developmental stages she has passed through supposedly imply consistency in how she will behave in morally relevant situations (see Doris, 2002). But it just isn't so.

Seemingly inconsequential situational changes can give rise to consequential behavioral inconsistencies. In a classic study by Darley and Batson (1973), for instance, students at the Princeton Theological Seminary – whose current mission statement lists "compassion" among its training objectives – failed to show exactly this quality in the face of a minor contextual change. The experiment required students to walk from one building to another. On the way, and believing that they were running late, merely 10% of the students offered help to a (confederate) person slumped in a doorway. When time was of little concern, however, 63% of them did so. This inconsistency in compassionate behavior is striking given the seemingly minor situational change. Although examples of such inconsistencies abound (Fleischhut and Gigerenzer, in press), the notion of stable virtues remains "deeply compelling" to most of us – notwithstanding the fact that "much of this lore rests on psychological theory that is some 2,500 years old" (Doris, 2002, p. ix).

The lore of stable and domain-general risk preferences arose in the twentieth century (for a canonical reference, see Samuelson, 1938), and it is at least as seductive as theories of robust and context-invariant moral traits and virtues. Without the assumption of stable preferences standard utility models in many fields of economics simply would not work. Yet evidence against this assumption has been mounting for decades (see Friedman and Sunder, 2011). Let us give just two recent examples. Contrary to expected utility theory, Tversky and Kahneman (1992) and Tversky and Fox (1995) showed that, depending on domain (loss versus gain) and probability (low versus high), people behave in both a risk-averse *and* a risk-seeking way. Specifically, they are risk-averse when the probability of winning is high but risk-seeking when it is low. In the loss domain, in contrast, people are risk-averse when the probability of losing is low but risk-seeking when it is high (**Table 1**). This "fourfold pattern" runs counter to the assumption of risk aversion as a domain-general trait. It has been shown to arise in *decisions from description* (Hertwig et al., 2004), where – as is common in choices between monetary gambles such as those used by Kahneman and Tversky (1979) – people are able to peruse descriptions of probability and outcome distributions. Outside the laboratory, however, outcomes and probabilities are rarely known with certainty and served up to the decision-maker on a platter. Consequently, people must often choose between options without having a convenient description of possible choice outcomes, let alone their probabilities. One strategy for overcoming such uncertainty is to sample the payoff distributions to learn about the options' attractiveness and, based on the experienced information, to come to a decision. In such *decisions from experience* (Hertwig and Erev, 2009) the fourfold pattern is reversed (**Table 1**; see also Hertwig, 2011). In other words, inferred risk preferences vary as a function of the mode of decision making (description versus experience) as well as domain (gain versus loss) and probability (low versus high).

Instability in risk preferences has also been found in real-world data. Starting with the assumption that people are expected utility maximizers, Barseghyan et al. (2011) examined whether the choice of insurance cover in a sample of U.S. households can be modeled by the same coefficient of absolute risk aversion. It could not. Households' inferred risk preferences proved to be unstable across highly related decision contexts, differing not only between auto insurance and home insurance but also between two different types of auto insurance (collision versus comprehensive).

## HOW TO MODEL INCONSISTENCIES IN BEHAVIOR

Perhaps the most common response to these demonstrations of unstable risk preferences has been to increase the flexibility of expected utility theory while retaining its original scaffolding. Flexibility comes in the form of additional adjustable parameters. To take one prominent example, cumulative prospect theory (Tversky and Kahneman, 1992) has five adjustable parameters, which allow both for separate value functions for losses and gains and for a probability-weighting function to accommodate the fourfold pattern. In this approach, any further inconsistencies in risk preferences (e.g., Barseghyan et al., 2011) would require additional adjustable parameters – for instance, a parameter that accommodates risk aversion as a function of different insurance domains. Similar attempts to "repair" expected utility theory (Selten, 2001) in light of contrary evidence include introducing error terms into utility models (e.g., Hey and Orme, 1994) and assuming stochastic preferences (e.g., the random preference model; Loomes and Sugden, 1995). The problems with this approach have become obvious. Parameterized repair models, which already assume complex computations, become even more opaque *as-if* models that cannot describe the underlying decision process.

**Table 1 | Fourfold pattern in decisions from description and reversed pattern in decisions from experience (Hertwig, 2011).**

| | Description | | Experience | |
|---|---|---|---|---|
| **Probability** | **Gain** | **Loss** | **Gain** | **Loss** |
| Low | $C$(100,0.05)[a] = 14, risk-seeking | $C$(–100,0.05) = –8, risk aversion | 32, 0.1 versus 3, 1.0, Risk aversion (20%[b]) | –32, 0.1 versus –3, 1.0, Risk-seeking (72%) |
| High | $C$(100,0.95) = 78, risk aversion | $C$(–100,0.95) = –84, risk-seeking | 4, 0.8 versus 3, 1.0, Risk-seeking (88%) | –4, 0.8 versus –3, 1.0, Risk aversion (44%) |

[a] *C(100,0.05) represents the median certainty equivalent for the gamble to pay $100 with probability p = 0.05, otherwise nothing (based on Tversky and Fox, 1995).*

[b] *Choice proportions refer to the percentage of choices of the risky option in each pair of gambles (based on Hertwig et al., 2004; Hertwig, 2011).*

It is time to move out of this theoretical cul-de-sac. The alternative we propose is to replace the concept of preferences by that of heuristics or, more generally, of cognitive strategies that give rise to diverse behavioral patterns. By "heuristic" we mean a strategy that ignores part of the information in order to make decisions faster and more accurately (Gigerenzer and Gaissmaier, 2011). Although inconsistent behavior presents a problem for the notion of stable preferences, for the framework of heuristics it does not. On the contrary, heuristics imply what looks like inconsistent behavior and can even predict when it will occur. A person who consistently relies on the same heuristic can behave in a seemingly inconsistent way. The inconsistency does not reside, however, in the person; it arises from looking at behavior through the lenses of a theory that assumes stable preferences.

## HOW LEXICOGRAPHIC HEURISTICS IMPLY INCONSISTENCIES

Heuristics enable one to model choices indicative of inconsistent risk preferences in terms of the sequential processing steps and the interactions between the heuristic and the choice environment. For illustration, consider the *priority heuristic* (Brandstätter et al., 2006, 2008), which belongs to the class of lexicographic rules. The heuristic is composed of the following steps (for generalization to loss gambles and multiple outcomes, see Brandstätter et al., 2006):

> *Search rule.* Go through the considerations in the following order: minimum gain, probability of minimum gain, maximum gain.
> *Stopping rule.* Stop examination if the minimum gains differ by 1/10 (or more) of the maximum gain; otherwise, stop examination if probabilities differ by 1/10 (or more) of the probability scale.
> *Decision rule.* Choose the gamble with the more attractive gain (probability). The more attractive gamble is that with the higher (minimum or maximum) gain and the lower probability of leading to the minimum gain.

To demonstrate how the heuristic works, let us return to the fourfold pattern. **Table 1** (left panel) reports certainty equivalents C, which represent the amount of money for which a person proves to be indifferent between a risky gamble and the certain amount C. Consider, for instance, the upper-left cell. The median C of $14 exceeds the expected value of the risky gamble ($5,100 with a probability of 5%). People are thus interpreted to be risk-seeking because of their preference for the risky gamble over the sure gain of $5. This information thus lends itself to the construction of choice problems such as the following:

A: 100 with $p = 0.05$
0 with $p = 0.95$
B: 5 with $p = 1$

To predict the majority choice in this gamble, the priority heuristic starts by comparing the minimum gains (0 and 5). The difference in the minimum gain, $5, does not reach the aspiration level of 10 (1/10 of 100) and so fails to discriminate between the options. Consequently, the probabilities of the minimum gains are examined next. These do not discriminate either (1.0–0.95 < 0.10). Therefore, the heuristic turns to the maximum gains (100 and 5) and predicts that the option that offers the higher gain (the risky option) is chosen. This choice, which accords with the certainty equivalent of $14 (**Table 1**), implies risk-seeking.

Without resorting to non-linear transformations of quantities or to other adjustable parameters, the priority heuristic can correctly predict the entire fourfold pattern of risk preferences in decisions from description and in fact logically implies it (Katsikopoulos and Gigerenzer, 2008). The key to its predictive power is the sequential activation of several classic heuristics. Specifically, in the domain of gains, the heuristic's first consideration is the only one examined by the *minimax heuristic,* which embodies risk aversion through its policy of always selecting the option with the highest minimum payoff. Unlike minimax, however, the priority heuristic bases its choice on the minimum outcomes only when the difference between them exceeds an aspiration level. If this aspiration level is not reached, then only the second consideration, the probability of the minimum outcome, is attended to. This consideration captures the policy of the *least likely heuristic*, which embodies risk aversion by identifying each gamble's worst outcome and selecting the gamble with the lowest probability of leading to the lowest payoff. Again, the priority heuristic takes advantage of an aspiration level to "evaluate" whether this policy is reasonable. If not, it shifts gears and consults the last consideration, the maximum outcomes. This is the home turf of the *maximax heuristic,* which chooses the gamble with the highest monetary payoff, thus implementing unconditional risk-seeking.

The priority heuristic thus integrates three classic heuristics into one and works through them sequentially. As a result, it can produce risk-averse or risk-seeking choices, depending on the number of considerations that a particular choice problem requires the heuristic to examine. Moreover, depending on the specific sequence of successive choice problems, a user of the heuristic may seem to act risk-averse one minute and risk-seeking the next only to switch back to what appears to be aversion again. This pattern of behavior does not reflect unstable risk preferences, however, but rather follows directly from the interaction of the heuristic's architecture with the choice environment. Admittedly, one could still defend the notion of a general risk disposition by arguing that risk-averse or risk-seeking people choose different heuristics from their adaptive toolbox. But if that were true, then risk-averse people should consistently use minimax and risk-prone people maximax – not the priority heuristic. The evidence does not support this conjecture (Brandstätter et al., 2006). Finally, note that the priority heuristic, like any heuristic, is not a domain-general strategy. It operates on explicitly stated (described) probabilities, and thus cannot explain the reversed fourfold pattern in decisions from experience (**Table 1**; for a psychological account of this class of decisions see, for instance, Gonzalez and Dutt, 2011).

## HOW HEURISTICS IN THE SOCIAL WORLD IMPLY BEHAVIORAL INCONSISTENCIES

The interaction between a heuristic and the environment may also be the key to understanding apparent behavioral inconsistencies in morally relevant situations. For illustration, consider the *equity heuristic* (Hertwig et al., 2002), according to which parents divide their resources among their *n* children equally in any given investment interval. The heuristic can produce both equal and unequal cumulative distributions of parental resources and thus a fairer or less fair outcome. It does not, however, create both equality and inequality through inconsistent preferences. Instead, depending on the environment – specifically, the number of children, their birth order, and the size of interbirth intervals – the equity heuristic implies equal or unequal investments across children. The case of organ donation illustrates how another simple strategy, the *default heuristic*, can produce predominantly altruistic behavior in "opt-out" countries such as France and Austria and predominantly non-altruistic behavior in Germany and the Netherlands, where people must "opt in" to be donors. Again, the drastically different hypothetical organ donation rates are not a reflection of inconsistent preferences or traits in neighboring societies but rather the product of the interaction between an environment (here, the legal default) and the heuristic (which accepts the default; Fleischhut and Gigerenzer, in press).

## CONCLUSION

Inconsistencies in observed behavior have been interpreted as conflicting with assumed stable preferences or traits. According to our analysis, the problem lies not in the inconsistent behavior but in the assumed existence of preferences, whether stable, probabilistic, or of another kind. We show that a theoretical analysis that explains behavior as a function of heuristics' interactions with the environment can do more than describe seeming behavioral inconsistencies *post hoc*; it can predict precisely when such inconsistencies will occur.

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## REFERENCES

Barseghyan, L., Prince, J., and Teitelbaum, J. C. (2011). Are risk preferences stable across contexts? Evidence from insurance data. *Am. Econ. Rev.* 101, 591–631.

Brandstätter, E., Gigerenzer, G., and Hertwig, R. (2006). The priority heuristic: Making choices without tradeoffs. *Psychol. Rev.*113, 409–432.

Brandstätter, E., Gigerenzer, G., and Hertwig, R. (2008). Risky choice with heuristics: reply to Birnbaum (2008), Johnson, Schulte-Mecklenbeck, and Willemsen (2008) and Rieger and Wang (2008). *Psychol. Rev.*115, 281–290.

Darley, J. M., and Batson, C. D. (1973). From Jerusalem to Jericho: a study of situational and dispositional variables in helping behavior. *J. Pers. Soc. Psychol.* 27, 100–108.

Doris, J. M. (2002). *Lack of Character: Personality and Moral Behavior*. New York: Cambridge University Press.

Fehr, E., and Schmidt, K. M. (1999). A theory of fairness, competition, and cooperation. *The Quarterly Journal of Economics* 114, 817–868.

Fleischhut, N., and Gigerenzer, G. (in press). "Beyond character: social heuristics explain moral behavior," in *Simple Heuristics in a Social World*, eds R. Hertwig, U. Hoffrage, and the ABC Research Group (New York: Oxford University Press).

Friedman, D., and Sunder, S. (2011). *Risk Curves: From Unobservable Utility to Observable Opportunity Sets (June 6, 2011). Yale Economics Department Working Paper*. Available at: http://ssrn.com/abstract=1858769

Gigerenzer, G., and Gaissmaier, W. (2011). Heuristic decision making. *Ann. Rev. Psychol.* 62, 451–482.

Gonzalez, C., and Dutt, V. (2011). Instance-based learning: integrating sampling and repeated decisions from experience. *Psychol. Rev.* 118, 523–551.

Hertwig, R. (2011). The psychology and rationality of decisions from experience. *Synthese*. doi: 10.1007/s11229-011-0024-4

Hertwig, R., Barron, G., Weber, E. U., and Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychol. Sci.*15, 534–539.

Hertwig, R., Davis, J. N., and Sulloway, F. J. (2002). Parental investment: how an equity motive can produce inequality. *Psychol. Bull.*128, 728–745.

Hertwig, R., and Erev, I. (2009). The description-experience gap in risky choice. *Trends Cogn. Sci.* 13, 517–523.

Hey, J. D., and Orme, C. (1994). Investigating generalizations of expected utility theory using experimental data. *Econometrica* 62, 1291–1326.

Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–292.

Katsikopoulos, K. V., and Gigerenzer, G. (2008). One-reason decision-making: Modeling violations of expected utility theory. *J. Risk Uncertain.* 37, 35–56.

Kohlberg, L. (1984). *Essays in Moral Development*: *The Psychology of Moral Development*, Vol. 2. New York: Harper & Row.

Loomes, G., and Sugden, R. (1995). Incorporating a stochastic element into decision theories. *Eur. Econ. Rev.* 39, 641–648.

Samuelson, P. (1938). A note on the pure theory of consumers' behaviour. *Economica* 5, 61–71.

Selten, R. (2001). "What is bounded rationality?" in *Bounded Rationality: The Adaptive Toolbox*, eds G. Gigerenzer and R. Selten (Cambridge, MA: MIT Press), 13–36.

Tversky, A., and Fox, C. R. (1995). Weighing risk and uncertainty. *Psychol. Rev.* 102, 269–283.

Tversky, A., and Kahneman, D. (1992). Advances in prospect theory: cumulative representation of uncertainty. *J. Risk Uncertain.* 5, 297–232.

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# Preference stability and memory: two unlikely companions

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Do people have stable risk preferences? This important question has engaged normative (von Neumann and Morgenstern, 1947) and both computational (e.g., Kahneman and Tversky, 1979, 1992; Tversky and Koehler, 1994; Birnbaum, 2008) and non-computational descriptive theories of judgment and decision-making (e.g., Brandstätter et al., 2006). The above theories differ, among other aspects, in how they conceptualize decision-making in general and risk preferences in particular. For instance, decision-making under uncertainty has been thought of as either a rational process through which an agent maximize "utility" (the perceived goodness of an option) or a process that translates objective, external utility into stable internal, subjective value. The stability (or instability) of risk preferences emerges as a by-product of such processes and conceptualization.

Here we would like to take a step back and consider the question from a different angle. A discussion about preference stability raises the question: where does the stability come from? If we start with the assumption that people have stable risk preferences, which cognitive processes underlie stable risk preferences? One obvious candidate for the origin of preference stability is memory. We need to remember – to some level or other – that we like something (e.g., wine) so to be able to prefer it to something that we like less (e.g., cider). In order to be able to make a choice between two options we at least need to be able to keep both options in short-term memory (STM) for long enough to make the decision. From a more long-term perspective the choices we have made – and tend to make – need to be remembered in order to reduce or avoid cognitive dissonance (Festinger, 1957) and develop a sense of self. LeDoux (1996, 2002) argues that the self is a representational structure emerging from integrative memory processes. We are one because our memory holds the pieces together, and it lets us integrate in the myriad of experiences we have, the things we see and the aspirations we have. Memory influences decision-making even when judgments are made "on-line" (i.e., while experiencing the to-be-assessed experience) and relying on memory becomes a relatively costly cognitive process (Aldrovandi et al., 2009, 2011; for a review, see Hastie and Park, 1986). Accessibility – the influence of the most easily retrievable information on judgment (e.g., Kahneman and Tversky, 1979) – is so ubiquitous in its influence on judgments and decision tasks, that it is generally considered as a truism (cf. Schwarz and Vaughn, 2002). Most approaches and models therefore include memory processes amongst the cognitive precursors of judgment biases (e.g., Dougherty et al., 1999; Stewart et al., 2006; Weber and Johnson, 2006).

Thus, if we accept the claim that memory has a strong influence on judgments and decision-making, the question is then whether memory processes sustain the stability of our preferences across situations, contexts, and stimuli? We feel that the answer to this question is a resounding "no." In a nutshell, our memories are not stable, they are influenced by motivational and situational factors and they are highly malleable and changeable. Memory formation, encoding, and retrieval are susceptible to bias and it is increasingly accepted that affective states are highly reconstructive (e.g., Kemp et al., 2008). In this opinion letter, we will make three observations on why memory cannot sustain stability for risk preferences. First, we will discuss how memory biases how we summarize the quality of recent experiences – hence influencing our choices and leading to preference instability. Second, memories for our preferences are highly distorted and highly reconstructed – do we really remember what we prefer or do we prefer what we chose? Third, we will reflect on how long-term memory (LTM; what we know) influences STM (short-term memory; what we remember from a recent experience) – "filling in the gaps" and hence potentially decreasing the correspondence between experience and choice.

Let's start with the discrepancy between experienced and remembered utility. How we summarize the quality of an experience can be very different from what we actually experienced. The work by Kahneman and colleagues suggests that how people summarize experiences in hindsight drives the choices they will make in the future; for instance, retrospective evaluations appear to be an important input into decisions to repeat (or not repeat) past experiences (e.g., Kahneman et al., 1993; Kahneman, 2000; Kahneman and Thaler, 2006). In medical settings, this influence of our memory can lead people to take bad choices and increase risk-taking. For instance, a large proportion of women who do not attend routine mammogram screening mention the remembered pain of previous screenings as the reason for their decision (Baines et al., 1990; Elwood et al., 1998). More strikingly, about 40% of patients who survived a cardiac arrest decide not to undergo future revival procedures – and again this choice was largely due to the remembered discomfort of the treatment (Bedell et al., 1983). However, would people always take these risks? Evidence suggests that the same category of unpleasant and/or painful medical procedures can be remembered very differently, and that decisions about these can largely differ as a consequence. In an oft-cited clinical study, Redelmeier et al. (2003) showed that adding an extra period of pain can actually improve the evaluation of a painful medical procedure. Patients undergoing colonoscopy were randomly assigned to either a control group, who underwent the standard procedure, or an experimental group. In the latter condition, the procedure was extended by leaving the apparatus in place for an average 2 min after the clinic examination was completed. This added experience was mildly uncomfortable – but less painful than the preceding moments. As a result, the experimental group rated the colonoscopy as a whole as less painful than patients in the control group; the authors argued that this result was due to the final moments (recency in memory) being largely overweighed. Confirming the link between memory and decision-making, the patients from the experimental group were more likely to comply with screening recommendations – and hence less likely to take the risky decision of forgoing future screening. On the same principle, Aldrovandi et al. (2011) showed that simply inserting a 10-s interval between items presentation and evaluation largely reduces the impact of a negative word on the pleasantness rating for the list as a whole. A subsequent recall task showed that memory functioning was responsible for these evaluations – as the delay effect on judgment was mediated by the drop in recall for the recency item (e.g., Bjork and Whitten, 1974). One could argue that memory biases retrospective evaluations only with affective and experiential stimuli, where it is possibly arduous to "extract" utility for each segment of the to-be-assessed experience. However, similar biases have also been observed with monetary sequences (pay outs; Langer et al., 2005), where one would expect affect to play less of a role and utility maximization to have a stronger effect. As a final and related point, preferences depend also on temporal proximity. The temporal proximity hypothesis (Soman, 2003) states that early (late) negative instances lower prospective (retrospective) evaluations more than late (early) ones. When evaluating an unfolding event, either primacy – for prospective evaluations – or recency effects – for retrospective ones – are observed.

Our memories for our preferences are distorted and highly reconstructed – more in hindsight to justify the decisions than with foresight to determine what decisions we will take. Indeed, once a choice is made, how aware are people of the reasons that drove their decision-making? How much correspondence is there between the reasons that influence decision-making and those reported in retrospect? If people "construct" (cf. Shafir et al., 1993) reasons in order to make a decision, it could be argued that such reasons are available after an option is selected (or rejected). Recent evidence seems to suggest that people can be rather inaccurate in this respect. When thinking back about a choice scenario, it seems that people justify their decision-making depending on what they believe their choice was – rather than their actual choice (Johansson et al., 2005; Henkel and Mather, 2007). Strikingly, people can go a full length in order to justify a choice they actually did not make, but were made to believe they did (Johansson et al., 2005). This meta-cognition inaccuracy about decisions seems also to influence memory for the features of the options in the choice scenario. Henkel and Mather (2007) showed that positive features are more likely to be remembered as associated with the chosen option – regardless of it being true or not (see also Brehm, 1956). Potentially, fuzzy-trace theory (FTT; Brainerd and Reyna, 1992) offers a memory-based theoretical framework to explain this apparent dissociation between recall and judgment – and why people can be so inaccurate when thinking back about their decision-making. According to FTT, encountered information is encoded in two parallel – and independent – ways. On the one hand verbatim information includes item-specific and episodic aspects of the information. On the other hand, people encode a gist, a "general picture" of the information where the specific details are somehow more blurred. As these two different forms of representation are encoded, stored, and retrieved in an independent manner, dissociations can be easily observed. In the context of decision-making, if we assume that people make choices mostly on the basis of the gist they encode about the choice scenario, then it can be explained how they can be so inaccurate about its verbatim information (a similar approach is that of the value-account; Betsch et al., 2001). To sum up, memory for our preferences is highly distorted and reconstructed – and these qualities make preferences highly unstable. Also, preferences are functional in that they can be used in hindsight to justify the decisions taken; this means, though, that preferences themselves are not always accessed to determine our decision-making. Decisions are then vulnerable to situational and contextual factors, and instability in decision-making under uncertainty is readily explained.

The influence of LTM on current task performance has been demonstrated extensively in research on false memories (e.g., Roediger and McDermott, 1995; Norman and Schacter, 1997; McDermott and Watson, 2001). More recently, studies have shown similar effects of LTM on episodic and STM in the visual domain (Hemmer and Steyvers, 2009; Heussen et al., 2011). When people are asked to reproduce the size of an apple that they have seen a few seconds ago, they are influenced both by the average size of fruit and by the average size of apples. These studies suggest that the influence of semantic knowledge on current task performance might be more prevalent than previously thought. The results also suggest that the more inaccurate the STM for an experience or some information, the more we will resolve to use LTM to "fill the gaps." In contrast, when STM is accurate (e.g., in primacy and recency positions), then LTM plays less of a role (Heussen et al., 2011). The ubiquity of this influence of LTM raises the question whether we remember our own preferences or we construct them from the norms we have experienced. Do I really prefer skiing on prepared slopes to off-piste snowboarding or is it just what one is supposed to prefer, given a certain age and responsibility? Further, decisions about a just-experienced event can be very different depending on the accuracy of our memory over the short term – and how much it needs to rely on LTM.

Recent evidence has indicated that people do not have stable preferences for risk-taking, far from it. Many factors can influence the extent of one's tendency to take risky decisions; these include framing, accessibility in memory, and context among others (e.g., Kusev et al., 2009). Regarding the latter, a recent study has shown that people's risk preferences in financial settings were sensitive to context, i.e., to financial domain (Vlaev et al., 2010). The valence and complexity of the financial scenario influenced participants' decision-making. Risk preferences were stable within financial domains – e.g., positive (salary, gamble to win), negative (gamble to lose and insurance) and positive-complex domain (investment and mortgage) – but not across them. Participants did not display stable risk preferences; rather, they were largely influenced by the financial scenario at hand.

In conclusion, the evidence reviewed here suggests that although memory is clearly involved in the processes of judgments and decision, memory cannot be a good candidate to provide the stability of preferences. On the contrary, situational and contextual factors heavily influence memory processes and hence lead to unstable preferences. If preference stability does exist, memory is certainly not its basis.


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## REFERENCES


Aldrovandi, S., Poirier, M., Heussen, D., and Ayton, P. (2009). "Memory strategies mediate the relationships between memory and judgment," in *Proceedings of the 31st Annual Conference of the Cognitive Science Society*, eds N. A. Taatgen and H. van Rijn (Austin, TX: Cognitive Science Society), 2457–2462.

Aldrovandi, S., Poirier, M., Kusev, P., Heussen, D., and Ayton, P. (2011). "Now I like it, now I don't: delay effects and retrospective judgment," in *Proceedings of the 33rd Annual Conference of the Cognitive Science Society*, eds L. Carlson, C. Hoelscher, and T. F. Shipley (Austin, TX: Cognitive Science Society), 2866–2871.

Baines, C. J., To, T., and Wall, C. (1990). Women's attitudes to screening after participation in the National Breast Cancer Screening Study: a questionnaire survey. *Cancer* 65, 1663–1669.

Bedell, S. E., Delbanco, T. L., Cook, E. F., and Epstein, F. H. (1983). Survival after cardiopulmonary resuscitation in the hospital. *N. Engl. J. Med.* 309, 569–576.

Betsch, T., Plessner, H., Schwieren, C., and Gütig, R. (2001). I like it but I don't know why: a value-account approach to implicit attitude formation. *Pers. Soc. Psychol. Bull.* 27, 242–253.

Birnbaum, M. H. (2008). Evaluation of the priority heuristic as a descriptive model of risky decision making: comment on Brandstätter, Gigerenzer, and Hertwig (2006). *Psychol. Rev.* 115, 253–262.

Bjork, R. A., and Whitten, W. B. (1974). Recency-sensitive retrieval processes in long-term free recall. *Cogn. Psychol.* 6, 173–189.

Brainerd, C. J., and Reyna, V. F. (1992). Explaining "memory-free" reasoning. *Psychol. Sci.* 3, 332–339.

Brandstätter, E., Gigerenzer, G., and Hertwig, R. (2006). The priority heuristic: making choices without tradeoffs. *Psychol. Rev.* 113, 409–432.

Brehm, J. W. (1956). Post-decision changes in the desirability of alternatives. *J. Abnorm. Soc. Psychol.* 52, 384–389.

Dougherty, M. R. P., Gettys, C. F., and Ogden, E. E. (1999). MINERVA-DM: a memory processes model for judgments of likelihood. *Psychol. Rev.* 106, 180–209.

Elwood, M., McNoe, B., Smith, T., Bandaranavake, M., and Doyle, T. C. (1998). Once is not enough: why some women do not continue to participate in a breast cancer screening programme. *N. Z. Med. J.* 111, 180–183.

Festinger, L. (1957). *A Theory of Cognitive Dissonance*. Evanston, IL: Row & Peterson.

Hastie, R., and Park, B. (1986). The relationship between memory and judgement depends on whether the judgment task is memory-based or on-line. *Psychol. Rev.* 93, 258–268.

Hemmer, P., and Steyvers, M. (2009). Integrating episodic memories and prior knowledge at multiple levels of abstraction. *Psychon. B Rev.* 16, 80–87.

Henkel, L. A., and Mather, M. (2007). Memory attributions for choices: how beliefs shape our memories. *J. Mem. Lang.* 57, 163–176.

Heussen, D., Poirier, M., Hampton, J. A., and Aldrovandi, S. (2011). "An effect of semantic memory on immediate memory in the visual domain," in *European Perspectives on Cognitive Science: Proceedings of the European Conference on Cognitive Science*, eds B. Kokinov, A. Karmiloff-Smith, and N. J. Nersessian (Sofia: NBU Press). Article No: 134.

Johansson, P., Hall, L., Sikström, S., and Olsson, A. (2005). Failure to detect mismatches between intention and outcome in a simple decision task. *Science* 310, 116–119.

Kahneman, D. (2000). "Evaluations by moments: past and future," in *Choices, Values and Frames*, eds D. Kahneman and A. Tversky (New York: Cambridge University Press), 693–708.

Kahneman, D., Fredrickson, B. L., Schreiber, C. A., and Redelmeier, D. A. (1993). When more pain is preferred to less: adding a better end. *Psychol. Sci.* 4, 401–405.

Kahneman, D., and Thaler, R. H. (2006). Utility maximization and experienced utility. *J. Econ. Perspect.* 20, 221–234.

Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–291.

Kemp, S., Christopher, D. B. B., and Furneaux, L. (2008). A test of the peak-end rule with extended autobiographical events. *Mem. Cognit.* 36, 132–138.

Kusev, P., van Schaik, P., Ayton, P., Dent, J., and Chater, N. (2009). Exaggerated risk: prospect theory and probability weighting in risky choice. *J. Exp. Psychol. Learn. Mem. Cogn.* 35, 1487–1505.

Langer, T., Sarin, R. K., and Weber, M. (2005). The retrospective evaluation of payment sequences: duration neglect and peak-and-end effects. *J. Econ. Behav. Organ.* 58, 157–175.

LeDoux, J. E. (1996). *The Emotional Brain*. New York: Simon & Schuster.

LeDoux, J. E. (2002). *Synaptic Self: How Our Brains Become Who We Are*. New York: Viking.

McDermott, K. B., and Watson, J. M. (2001). The rise and fall of false recall: the impact of presentation duration. *J. Mem. Lang.* 45, 160–176.

Norman, K. A., and Schacter, D. L. (1997). False recognition in younger and older adults: exploring the characteristics of illusory memories. *Mem. Cognit.* 25, 838–848.

Redelmeier, D. A., Katz, J., and Kahneman, D. (2003). Memories of colonoscopy: a randomized trial. *Pain* 104, 187–194.

Roediger, H. L., and McDermott, K. B. (1995). Creating false memories: remembering words not presented in lists. *J. Exp. Psychol. Learn. Mem. Cogn.* 21, 803–814.

Schwarz, N., and Vaughn, L. A. (2002). "The availability heuristic revisited: ease of recall and content of recall as distinct sources of information," in *Heuristic and Biases*, eds T. Gilovich, D. Griffin, and D. Kahneman (New York: Cambridge University Press), 103–119.

Shafir, E., Simonson, I., and Tversky, A. (1993). Reason-based choice. *Cognition* 49, 11–36.

Soman, D. (2003). Prospective and retrospective evaluations of experiences: how you evaluate it depends on when you evaluate it. *J. Behav. Decis. Mak.* 16, 35–52.

Stewart, N., Chater, N., and Brown, G. D. A. (2006). Decision by sampling. *Cogn. Psychol.* 53, 1–26.

Tversky, A., and Kahneman, D. (1992). Advances in prospect theory: cumulative representation of uncertainty. *J. Risk Uncertain* 5, 297–323.

Tversky, A., and Koehler, D. J. (1994). Support theory: a nonextensional representation of subjective probability. *Psychol. Rev.* 101, 547–567.

Vlaev, I., Kusev, P., Stewart, N., Aldrovandi, S., and Chater, N. (2010). Domain effects and financial risk attitudes. *Risk Anal.* 30, 1374–1386.

von Neumann, J., and Morgenstern, O. (1947). *Theory of Games and Economic Behaviour*, 2nd Edn. Princeton, NJ: Princeton University Press.

Weber, E. U., and Johnson, E. J. (2006). "Constructing preferences from memory," in *The Construction of Preferences*, eds S. Lichtenstein and P. Slovic (New York: Cambridge University Press), 397–410.



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# On the stability of choice processes

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Decisions researchers generally agree that the method of elicitation – be it task format or response mode – has a huge impact on people's responses: different task formats, such as probabilities and frequencies (Gigerenzer and Hoffrage, 1995) – or decisions from description and experience (Hertwig et al., 2004), trigger drastically different behavior. Different response modes, such as choosing, pricing, and matching, have been shown to prompt substantial discrepancies in people's preferences (e.g., Lichtenstein and Slovic, 1971; Tversky et al., 1988). While these streams of research have received much attention, much less is known about the effects of task format in decisions from description, which have been the staple for decision researchers. Here the underlying assumption seems to be that task format has little or no effect on the choice process (Birnbaum, 2004; Birnbaum et al., 2008). When choices differ across experiments, such instabilities can always be modeled by (a) using flexible multi-parameter models that allow for the description of strikingly different choice data (see Brandstätter et al., 2008 for a discussion), or by (b) situating an editing phase prior to the selection phase (Kahneman and Tversky, 1979). In both attempts the core process – the weighting and summing of information – remains unaffected. I argue that both attempts seem unsatisfactory, since different task formats trigger fundamentally different choice processes in decisions from description. Instead of advocating single calculus models I propose an adaptive tool box view of risky choice (Gigerenzer et al., 1999; Brandstätter et al., 2008). The crucial question thus becomes: which task format triggers which choice process? To answer this question I concentrate on decisions from descriptions and on two fundamentally different accounts of risky choice: expected utility theory and its modifications, and the priority heuristic (Brandstätter et al., 2006).

Expected utility theory and its modifications are historically rooted in the work of Daniel Bernoulli, and these models rest on the assumption of weighting and summing of information. Examples are expected utility theory (von Neumann and Morgenstern, 1947), cumulative prospect theory (Tversky and Kahneman, 1992), and the transfer of attention exchange model (Birnbaum et al., 2008). Interpreted as process theories, expected utility theory, for example, predicts that people value payoffs with a utility function, multiply the utilities by the probabilities, sum the products, and finally select the gamble with the higher sum of weighted values. These theories, therefore, predict that people process information within each gamble, such that an overall evaluation for each gamble is made.

The priority heuristic, which represents a different class of models, builds on the work of Luce (1956), Simon (1957), Tversky (1969), and Selten (2001). It is a simple lexicographic semiorder strategy that implies several classic violations of expected utility theory that had previously been accounted for by modifications of expected utility theory (Brandstätter et al., 2006; Katsikopoulos and Gigerenzer, 2008). Across four different data sets with a total of 260 problems, the priority heuristic predicted the majority choice better than each of three modifications of expected utility did. A process test using reaction times further confirmed the heuristic's process predictions (Brandstätter et al., 2006).

To illustrate the heuristic, consider a choice between two simple gambles where each offers "a probability $p$ of winning amount $x$ and a probability $(1-p)$ of winning amount $y$." A choice between two such gambles contains four reasons for choosing: the maximum gain, the minimum gain, and their respective probabilities; because probabilities are complementary, three reasons remain: the minimum gain, the probability of the minimum gain, and the maximum gain. For choices between gambles having two non-negative outcomes (all outcomes are zero or positive), the heuristic consists of the following steps:

*Priority rule.* Go through reasons in the order of minimum gain, probability of minimum gain, maximum gain.

*Stopping rule.* Stop examination if the minimum gains differ by 1/10 (or more) of the maximum gain; otherwise, stop examination if probabilities differ by 1/10 (or more) of the probability scale.

*Decision rule.* Choose the gamble with the more attractive gain (probability).

One-tenth of the maximum gain represents the aspiration level for gains, and 0.1 that for probabilities[1]. Note, the aspiration level for gains is not fixed but changes with the maximum gain of the problem. For probabilities, which are bound between 0 and 1, the aspiration level of 0.1 is fixed. The term "attractive" refers to the gamble with the higher (minimum or maximum) gain and to the lower probability of the minimum gain. The heuristic does not use any nonlinear transformations of outcomes and probabilities but takes both in their natural currencies (i.e., objective cash amounts and objective probabilities). Unlike the expectation-type models, the priority heuristic predicts that people process information between rather than within gambles. For gambles involving losses, the term "gain" is replaced by "loss." For gambles with more than two outcomes, and gambles involving gains and losses ("mixed gambles"), see Brandstätter et al. (2006).

To illustrate the conceptual difference between an expectation-type model such as prospect theory and the priority heuristic (for details see Brandstätter and Gußmack, submitted), consider the following choice problem (Kahneman and Tversky, 1979).

A: 6,000 with $p = 0.001$
0 with $p = 0.999$
B: 3,000 with $p = 0.002$
0 with $p = 0.998$

Most people (73%) chose Gamble A. How does prospect theory explain this majority choice? The standard value function is concave for gains, which implies

[1]For the sake of simplicity, I disregard the idea that aspiration levels are rounded (for details see Brandstätter et al., 2006).

that the larger amount of 6,000 is devalued more than the smaller amount of 3,000 (i.e., compared to a linear value function). The standard value function, thus, predicts B but not A. Prospect theory must explain the choice of A by the overweighting of small probabilities. That is, the overweighting of 0.001 (compared to 0.002) must be stronger than the devaluation of 6,000 (compared to 3,000). Because the weighting function is not well-behaved near the endpoints (Kahneman and Tversky, 1979), consider the other possibilities of (a) underweighting, (b) linear weighting, and (c) ignoring small probabilities. Underweighting of small probabilities (captured by an S-shaped rather than an inverse S-shaped probability weighting function) implies the choice of B but not of A – as does a linear weighting function (due to the value function). Ignoring small probability outcomes predicts guessing, because the zero outcomes remain. None of these additional possibilities, therefore, can account for the choice of A. The same reasoning holds for cumulative prospect theory, since both prospect theories are identical for two-outcome gambles. According to (cumulative) prospect theory, only the minute difference between 0.001 and 0.002 can cause the choice of A.

For the priority heuristic, this difference is neglected. The heuristic first compares the minimum gains (0 and 0). Because they do not differ, the probabilities (0.999 and 0.998 or their logical complements 0.001 and 0.002) are compared. This difference falls short of the aspiration level (i.e., smaller than 0.1) and people are predicted to choose A, because of its higher maximum gain. Thus, the priority heuristic captures the majority choice by using comparisons between rather than within gambles.

Both the priority heuristic and prospect theory can model the majority choice. In the following I will investigate which of these two models better captures the majority choice. We will see that task format plays a key role in this endeavor. In the light of both models, I also investigate the effect of salience on people's choice processes.

## DIFFERENT FORMATS–DIFFERENT PROCESSES

### FORMAT EFFECTS IN PROCESS TRACING

Soon after the publication of the priority heuristic, studies investigating information search suggested that the priority heuristic might not capture the choice process (Glöckner and Betsch, 2008; Johnson et al., 2008; Glöckner and Herbold, 2011). Previous tests using eye-tracking or computerized process tracing techniques, such as Mouselab, usually employed neutral information display matrices in which columns represented alternatives, and rows attributes (Ford et al., 1989). Such matrices are neutral, because they favor neither search between nor within alternatives (gambles) or attributes (reasons). The above studies, in contrast, investigated information search by using gambles that were sharply separated: gambles were either placed in extra boxes (Glöckner and Betsch, 2008; Glöckner and Herbold, 2011) or separated by a line (Johnson et al., 2008). Unsurprisingly, such task formats foster search within but not between gambles – thereby favoring expected utility theory and its modifications. Information search measured through eye-tracking or Mouselab, further, may not be equated with information processing measured through think-aloud protocols (Ericsson and Simon, 1993).

To overcome this limitation, we used classic think-aloud protocols to measure the cognitive processes underlying violations of expected utility theory (Brandstätter and Gußmack, submitted). To ensure neutrality in task format, we employed the same format as in Kahneman and Tversky (1979):

| Alternative A | Alternative B |
|---|---|
| 0.1% chance to win €6,000 | 0.2% chance to win €3,000 |
| 99.9% chance to win nothing | 99.8% chance to win nothing |

What would you choose?

A ○ B ○

It should be noted that this format was intended to support prospect theory – not the priority heuristic. Results show that across all 14 one-stage problems taken from Kahneman and Tversky (1979), most of the protocols revealed that people process information between rather than within gambles – thus lending strong support to processes implied by the priority heuristic (Brandstätter and Gußmack, submitted). That is, it is the difference between 6,000 and 3,000 rather than the overweighting of small probabilities that determines the choice between €6,000 with probability 0.001 and €3,000 with 0.002. Taken together,(a) separated gambles in combination with tools that merely measure information search show that people search information within gambles, whereas (b) neutral task formats in combination with tools that measure deeper cognitive processing suggest that cognitive operations akin to those of the priority heuristic best explain violations of expected utility theory.

### SALIENCE EFFECTS

Salience, I propose, has a strong effect on choice processes. To estimate parameter values for cumulative prospect theory, Tversky and Kahneman (1992) used certainty equivalents inferred from choices. Certainty equivalents represent the amount of money at which a person is indifferent between taking a risky gamble or a sure amount. In their experiments participants made many similar choices between one uncertain prospect and many sure amounts. Hence, the sure amount varied, whereas the probability of the uncertain prospect remained constant (for a similar procedure see, e.g., Tversky and Fox, 1995; Kilka and Weber, 2001; Abdellaou et al., 2005). This method focuses attention on the varying element (i.e., outcomes), while the constant element (i.e., probability) is largely ignored. Why not put things the other way around? What would happen if participants always chose between the same sure amount and a gamble containing varying probability information? Prospect theory's qualitative features might be quite different.

To test this conjecture one study manipulated probability salience (Brandstätter and Kühberger, submitted). To this end, participants estimated the probability of an uncertain event; then they chose between a risky gamble containing the estimated probability (i.e., you win €50 if the uncertain event occurs, otherwise nothing) and a sure amount of equal expected value. Results differed markedly between the control condition, which contained the same problems in text format, and the probability salience condition. Supporting previous research, in the control condition, participants were risk-seeking for low probabilities and risk-averse for high ones. In the probability salience condition, the opposite pattern emerged, and participants were risk-averse for low probabilities and risk-seeking for high ones.

If winning was unlikely, participants thought that they would not win anyway and selected the sure amount over the gamble; if winning was likely, they chose the risky gamble. These findings suggest a reference point of $p = 0.5$ (i.e., winning is likely/unlikely) rather than reference points of $p = 0$ and $p = 1$. The fact that findings differ substantially for different task formats highlights the error in hoping to uncover (a) a general choice pattern underlying probability weighting and (b) a fixed order of reasons for the priority heuristic.

## CONCLUSION

Decision researchers generally agree that elicitation methods have a strong influence on people's choices. Undoubtedly, in decisions from description, models containing many free parameters or the editing of a choice problem can model task format effects – without changing the core process of weighting and summing. Both attempts seem unsatisfactory. I presented evidence showing that people use the priority heuristic when problems are presented in a neutral text format, but that they search within gambles when gambles are placed in separate boxes. Salience, further, triggers fundamentally different choice processes in decisions from description. Together these results suggest that people use a multitude of decision strategies, and the priority heuristic seems to be one key candidate from the adaptive toolbox of risky-choice-strategies.

## REFERENCES


Abdellaou, M., Vossmann, F., and Weber, M. (2005). Choice-based elicitation and decomposition of decision weights for gains and losses under uncertainty. *Manage. Sci.* 51, 1384–1399.

Birnbaum, M. H. (2004). Tests of rank-dependent utility and cumulative prospect theory in gambles represented by natural frequencies: Effects of format, event framing, and branch splitting. *Organ. Behav. Hum. Decis. Process.* 95, 40–65.

Birnbaum, M. H., Johnson, K., and Longbottom, J. L. (2008). Test of cumulative prospect theory with graphical displays of probability. *Judgm. Decis. Mak.* 3, 528–546.

Brandstätter, E., Gigerenzer, G., and Hertwig, R. (2006). The priority heuristic: making choices without trade-offs. *Psychol. Rev.* 113, 409–432.

Brandstätter, E., Gigerenzer, G., and Hertwig, R. (2008). Risky choice with heuristics: reply to Birnbaum (2008), Johnson, Schulte-Mecklenbeck, and Willemsen (2008), and Rieger and Wang (2008). *Psychol. Rev.* 115, 281–289.

Ericsson, K. A., and Simon, H. A. (1993). *Protocol Analysis. Verbal Protocols as Data*. Cambridge, MA: MIT Press.

Ford, J. K., Schmitt, N., Schlechtman, S. L., Hults, B. H., and Doherty, M. L. (1989). Process tracing methods: contributions, problems, and neglected research questions. *Organ. Behav. Hum. Decis. Process.* 43, 75–117.

Gigerenzer, G., and Hoffrage, U. (1995). How to improve Bayesian reasoning without instruction: Frequency formats. *Psychol. Rev.* 102, 684–704.

Gigerenzer, G., Todd, P. M., and the ABC Research Group. (1999). *Simple Heuristics that Make us Smart*. New York: Oxford University Press.

Glöckner, A., and Betsch, T. (2008). Do people make decisions under risk based on ignorance? An empirical test of the priority heuristic against cumulative prospect theory. *Organ. Behav. Hum. Decis. Process.* 107, 75–95.

Glöckner, A., and Herbold, A. K. (2011). An eye-tracking study on information processing in risky decisions: evidence for compensatory strategies based on automatic processes. *J. Behav. Decis. Mak.* 24, 71–98.

Hertwig, R., Barron, G., Weber, E. U., and Erev, I. (2004). Decisions from experience and the effect of rare events. *Psychol. Sci.* 15, 534–539.

Johnson, E. J., Schulte-Mecklenbeck, M., and Willemsen, M. C. (2008). Process models deserve process data: a comment on Brandstätter, Gigerenzer, and Hertwig (2006). *Psychol. Rev.* 115, 263–273.

Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–291.

Katsikopoulos, K. V., and Gigerenzer, G. (2008). One-reason decision-making. Modeling violations of expected utility theory. *J. Risk Uncertain.* 37, 35–56.

Kilka, M., and Weber, M. (2001). What determines the shape of the probability weighting function under uncertainty? *Manage. Sci.* 47, 1712–1726.

Lichtenstein, S., and Slovic, P. (1971). Reversals of preference between bids and choices in gambling decisions. *J. Exp. Psychol.* 89, 46–55.

Luce, R. D. (1956). Semiorders and a theory of utility discrimination. *Econometrica* 24, 178–191.

Selten, R. (2001). "What is bounded rationality?" in *Bounded rationality: The adaptive toolbox*, eds G. Gigerenzer and R. Selten (Cambridge, MA: MIT Press), 13–36.

Simon, H. A. (1957). *Models of Man*. New York: Wiley.

Tversky, A. (1969). Intransitivity of preferences. *Psychol. Rev.* 76, 31–48.

Tversky, A., and Fox, C. R. (1995). Weighing risk and uncertainty. *Psychol. Rev.* 102, 269–283.

Tversky, A., and Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *J. Risk Uncertain.* 5, 297–323.

Tversky, A., Sattath, S., and Slovic, P. (1988). Contingent weighting in judgmeint and choice. *Psychol. Rev.* 95, 1988, 371–384.

von Neumann, J., and Morgenstern, O. (1947). *Theory of Gambles and Economic Behavior*. Princeton, NJ: Princeton University Press.



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# Formalizing heuristics in decision-making: a quantum probability perspective

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One of the most influential research programs in psychology is that of Tversky and Kahneman's (1973, 1983) on heuristics and biases in decision-making. Two characteristics of this program are, first, compelling empirical demonstrations that in some decision-making situations naïve observers violate the rules of classic probability (CP) theory and, second, that corresponding behavior can be explained with simple heuristics. Tversky and Kahneman's work has led to a vast literature on what is the basis for psychological process in decision-making. Note that their work, however impactful, has not settled the debate of whether CP theory is suitable for modeling cognition or not. CP models have attracted enormous interest and they often do provide excellent coverage of cognitive processes (e.g., Oaksford and Chater, 2007; Griffiths et al., 2010; Tenenbaum et al., 2011).

The idea of heuristics is appealing. First, they are simple. The assumption that human cognition is based on heuristics partly avoids the computational intractability problems which plague some formal approaches (cf. Sanborn et al., 2010). Second, they often allow an understanding of one process in terms of theory developed for other cognitive processes. Consider the representativeness and availability heuristics. According to the representativeness heuristic, judgments of frequency are driven by similarity and according to the availability heuristic by the ease of identifying related instances in memory. Thus, with these heuristics, an explanation for decision-making becomes one of similarity or memory. Third, heuristics often have strong empirical support. Tversky and Kahneman's approach has been to motivate explanations based on heuristics by providing compelling demonstrations for violations of the standard approaches (in decision-making, CP theory). Other proponents of heuristic approaches have argued that heuristic schemes lead to better results (e.g., Gigerenzer and Todd, 1999).

There is nothing *wrong* with heuristic approaches. But, there is a sense in which theoreticians have a bias for cognitive models based on formal frameworks, whether it is Bayesian probability, formal logic, or the quantum probability (QP) theory, which we discuss (cf. Elqayam and Evans, 2011). The properties of formal frameworks are interconnected. For example, all expressions in classical probability theory are based on a handful of axioms. Thus, one cannot accept the psychological relevance of one expression, but reject another: they are all related to each other. By contrast, heuristics, however successful, are somewhat interchangeable. Postulating the relevance of the representativeness heuristic does not necessitate the relevance of the availability heuristic (Pothos and Busemeyer, 2009a).

The QP research program in psychology partly originated as an attempt to reconcile people's violations of CP theory in decision-making situations with formal theory and examine whether it is possible to express formally some of the key heuristics in decision-making. QP theory is a theory for assigning probabilities to observables (Isham, 1989). Physicists are happy to employ CP theory in most cases but they believe that, ultimately, QP theory is the more appropriate choice. CP theory works by defining a sample space and expressing probabilities in terms of subsets of this space. A key property of this approach is the commutative nature of events and subsequent order independence for probabilities assigned to the joint events. QP is a geometric approach to probability. Events correspond to different subspaces and probabilities are computed by projections to these subspaces (note that projections have been discussed before in psychology; Sloman, 1993). Crucially, this makes probability assessment potentially order and context dependent and, e.g. (a suitable definition of), conjunction can fail commutativity. This and related interference effects lead to interesting predictions from QP theory.

In the famous Linda experiment (Tversky and Kahneman, 1983), participants are told about Linda, who sounds like a feminist and are then asked to judge the probability of statements about her. The important comparison concerns the statements "Linda is a bank teller" and "Linda is a feminist and a bank teller." The first statement is extremely unlikely. The second statement is a conjunction of the first statement and another one. Thus, according to CP theory, $P(\text{bank teller}) \geq (\text{bank teller feminist})$. But, results violate CP theory, as most participants consider the statement "Linda is a bank teller and a feminist" as the more probable one (this is called the conjunction fallacy). Tversky and Kahneman's explanation was that cognitive process is not based on CP theory, rather, participants employ a representativeness heuristic. They consider Linda as a very typical feminist, so that the characterization "bank teller and feminist" is probable, regardless of the bank teller part. One could also invoke an availability heuristic (as Tversky and Koehler, 1994 later did), whereby the statement "bank teller and feminist" activates memory instances similar to Linda.

**Figure 1** illustrates the QP theory explanation of the conjunction fallacy. The state vector is labeled as Psi and corresponds to what participants learn about Linda from the story. One 1D subspace corresponds to Linda being a feminist and another to a bank teller. We compute the probability for each possibility by projecting the state vector onto the corresponding subspace and squaring the length of the projection. If participants are asked to evaluate the probability that Linda is a just bank teller or just a feminist this is very unlikely and likely respectively. In QP theory, conjunction has to be typically defined as a sequential operation, i.e., $\text{Prob}(A \wedge B) \equiv \text{Prob}(A \wedge \text{then } B)$.

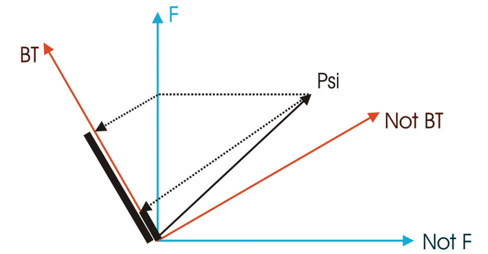


**FIGURE 1 | A simple explanation for how QP theory can account for the conjunction fallacy.**

Assume that in decision-making the more probable statement is evaluated first (this means that more probable statements are more likely to be included in the decision-making process; cf. Gigerenzer and Todd, 1999). Then, the probability computation involves projecting first to the feminist ray and then to the bank teller ray. The first projection is fairly large, we knew this already. The critical point is that from the feminist ray, there is now a sizeable projection onto the bank teller ray. Thus, whereas the direct projection to the bank teller one was small, the indirect projection (via the feminist ray) is much larger. Such a scheme can account for violations of the conjunction fallacy (and many other related empirical results; Busemeyer et al., 2011).

What is the implication about psychological process implied in the quantum theory model? In classical probability theory it has to be the case that Prob(bank teller $\wedge$ feminist) = Prob(feminist $\wedge$ bank teller) $\leq$ Prob(bank teller). But in QP theory, when considering possibilities which are represented by subspaces at oblique angles as in **Figure 1**, the assessment of *any* possibility is dependent on the assessment of previous possibilities. In the case of the conjunctive statement in the Linda problem, assessing the possibility that Linda is a bank teller depends on the previous consideration that Linda is a feminist. Clearly, the Linda story makes it very unlikely that Linda is a bank teller. But, feminists can have all kinds of different professions and, even though being a bank teller is perhaps not the most likely one, it is still a plausible profession. Therefore, once a participant has accepted that Linda is a feminist, it becomes easier to think of various professions for Linda, including that of a bank teller. That is, according to the quantum model, accepting Linda as a feminist, allows the system to establish a similarity between the initial representation (the initial information about Linda) and the representation for a bank teller. From a quantum theory perspective, representativeness, being a similarity process, is subject to chain and context effects, and this is exactly what happens in the Linda example. An alternative perspective is that seeing Linda as a feminist increases availability for other related information about Linda, such that Linda might be a bank teller. Briefly, this is the quantum theory explanation for the conjunction fallacy (Busemeyer et al., 2011).

Quantum probability theory has been applied in other decision-making situations (e.g., Trueblood and Busemeyer, 1992; Atmanspacher et al., 2004; Khrennikov, 2004; Aerts, 2009). We next consider an application which illustrates a different aspect of the theory. According to the sure-thing principle, if you intend to do A when B is true and you intend to do A when B is not true, then you should still intend to do A if you do not know if B is true or not. The sure-thing principle follows from the law of total probability in CP theory, $P(A) = P(A \wedge B) + P(A \wedge \text{not } B)$. Surprisingly, Shafir and Tversky (1992) reported violations of the sure-thing principle in a prisoner's dilemma task. In their experiment, the matrix of payoffs was set up so that participants preferred to defect, knowing that the other person had already defected and knowing that the other person had cooperated. However, many participants reversed their judgment and decided to cooperate, when they did not know the other player's action. Such a finding can be partly explained with cognitive dissonance theory (e.g., Festinger, 1957), according to which people change their beliefs to be consistent with their actions. Thus, if participants have a cooperative bias, in the "unknown" condition, they might be cooperating because they imagine the other person is willing to cooperate as well (Shafir and Tversky, 1992, called this idea wishful thinking). One could also apply Tversky and Shafir's (1992) suggestion that violations of the sure-thing principle can arise from a failure of consequential reasoning (this idea was put forward for the two-stage gambling task). In the known-defect situation there is a good reason to defect and likewise for the known – cooperate situation. But, in the unknown conditions it is as if the (separate) good reasons for defecting under each known condition cancel out (Busemeyer and Bruza, 2011, Chapter 9)!

Pothos and Busemeyer (2009a,b) created a quantum and classical model for violations of the sure-thing principle. Both models assumed that the state vector in the unknown case is a convex combination of the states in the known-defect and known-cooperate cases. Then, there is a process of evolving the state according to the relative payoff for different options and the cognitive dissonance principle. In both the QP and the CP case, the probability of defecting is determined by this evolved state. But, in the classic case, whatever the process of evolution, the evolved representation (vector) is still a convex combination of the known-defect, known-cooperate cases, which means that the CP model is always constrained by the law of total probability. By contrast, in the QP case probabilities are determined from the state vector by a squaring operation. For example, $|a+b|^2 = a^2 + b^2 + a^*b + b^*a$ The last two terms are interference terms and they can be negative, so that $|a + b|^2 < a^2 + b^2$, violating the law of total probability. Thus, the QP model allows an expression of the idea that individually perfectly good reasons or causes (high $a^2$, high $b^2$) can partly cancel each other out. Note, further, that although the utility representation in the quantum model is simple (there is a utility parameter, analogous to that in more standard decision models, like Kahneman and Tversky's, 1979, prospect theory), the possibility of interference effects would allow, e.g., a consistent preference for a risky option, over the sure-thing (i.e., a stable risk preference).

These are promising results for QP theory. Its features which make us optimistic are that probability assessment is context- and order-dependent, so that earlier components in a process can affect later ones.

In fact, such features are implied in some powerful heuristics, such as representativeness and availability. Quantum theory provides a promise that the intuitions for such heuristics could be described in a formal framework.

## REFERENCES


Aerts, D. (2009). Quantum structure in cognition. *J. Math. Psychol.* 53, 314–348.

Atmanspacher, H., Filk, T., and Romer, H. (2004). Quantum zero features of bistable perception. *Biol. Cybern.* 90, 33–40.

Busemeyer, J. R., and Bruza, P. (2011). *Quantum Models of Cognition and Decision Making*. Cambridge: Cambridge University Press.

Busemeyer, J. R., Pothos, E. M., Franco, R., and Trueblood, J. (2011). A quantum theoretical explanation for probability judgment errors. *Psychol. Rev.* 118, 193–218.

Elqayam, S., and Evans, J. S. (2011). Subtracting "ought" from "is": descriptivism versus normativism in the study of the human thinking. *Behav. Brain Sci.* 233–248.

Festinger, L. (1957). *A Theory of Cognitive Dissonance*. Stanford: Stanford University Press.

Gigerenzer, G., and Todd, P. M. (1999). *Simple Heuristics that Make us Smart*. New York: Oxford University Press.

Griffiths, T. L., Chater, N., Kemp, C., Perfors, A., and Tenenbaum, J. B. (2010). Probabilistic models of cognition: exploring representations and inductive biases. *Trends Cogn. Sci.* 14, 357–364.

Isham, C. J. (1989). *Lectures on Quantum Theory*. Singapore: World Scientific.

Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–291.

Khrennikov, A. Y. (2004). *Information Dynamics in Cognitive, Psychological, Social and Anomalous Phenomena*. Kluwer Academic.

Oaksford, M., and Chater, N. (2007). *Bayesian Rationality: The Probabilistic Approach to Human Reasoning*. Oxford: Oxford University Press.

Pothos, E. M., and Busemeyer, J. R. (2009a). The fallacy of normativism: falling in love with ourselves. A case for limited prescriptive normativism. *Behav. Brain Sci.*

Pothos, E. M., and Busemeyer, J. R. (2009b). A quantum probability explanation for violations of "rational" decision theory. *Proc. R. Soc. B* 276, 2171–2178.

Sanborn, A. N., Griffiths, T. L., and Navarro, D. J. (2010). Rational approximations to rational models: alternative algorithms for category learning. *Psychol. Rev.* 117, 1144–1167.

Shafir, E., and Tversky, A. (1992). Thinking through uncertainty: nonconsequential reasoning and choice. *Cogn. Psychol.* 24, 449–474.

Sloman, S. A. (1993). Feature-based induction. *Cogn. Psychol.* 25, 231–280.

Tenenbaum, J. B, Kemp, C., Griffiths, T. L., and Goodman, N. (2011). How to grow a mind: statistics, structure, and abstraction. *Science* 331, 1279–1285.

Trueblood, J. S., and Busemeyer, J. R. (1992). A comparison of the belief-adjustment model and the quantum inference model as explanations of order effects in human inference. *Cogn. Sci.* 1166–1171.

Tversky, A., and Kahneman, D. (1973). Availability: a heuristic for judging frequency and probability. *Cogn. Psychol.* 5, 207–232.

Tversky, A., and Kahneman, D. (1983). Extensional versus intuitive reasoning: the conjuctive fallacy in probability judgment. *Psychol. Rev.* 90, 293–315.

Tversky, A., and Koehler, D. J. (1994). Support theory: a nonextensional representation of subjective probability. *Psychol. Rev.* 101, 547–567.

Tversky, A., and Shafir, E. (1992). The disjunction effect in choice under uncertainty. *Psychol. Sci.* 3, 305–309.



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# Utility versus pleasure: the grand paradox

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Consider the following experimental demonstration: when undergraduate volunteers judged the pleasantness of winning small amounts of money (from 1 to 30 cents per trial), their successive ratings reflected the position of each winning in the frequency distribution of their other winnings (Parducci, 1968).

**Table 1** shows how the different distributions were skewed. Ratings of individual payoffs are not shown, for the present interest centers on the overall mean rating for each of the distributions. The overall mean rating on a 7-point scale was more than one category higher for the negatively skewed distribution (in which the higher winnings were more frequent), although the mean winning was 14 cents for each distribution). More generally, negatively skewed distributions always yield higher overall mean judgments. This is entailed by my range–frequency theory of judgment and supported by experiments on various kinds of hedonic and psychophysical judgments (Parducci, 1995).

## RANGE–FREQUENCY THEORY

The basic notion of the theory is that each dimensional judgment represents the place of what is being judged in a context of similar events that affect the judgment. This is represented as a compromise or weighted average:

$$J_{ic} = wR_{ic} + (1 - w)F_{ic} \tag{1}$$

where $J_{ic}$ represents the internal judgment (e.g., experienced pleasantness) of Stimulus $i$ in Context $c$, $R_{ic}$ is the proportion of the contextual range below $i$, $F_{ic}$ is the cumulative proportion of contextual representations below $i$ in the same context, and $w$ is the weighting constant, assumed here to be 0.5, with $J$, $R$, $F$, and $w$ all on 0-to-1 scales. From this, it follows algebraically that the mean of the judgments of all contextual values (winnings in this case) is proportional to the skewing of the contextual distribution.

When applied to this experimental demonstration, the mean of all judgments (ratings transformed linearly to a 0-to-1 scale) is predicted to be 0.58 for the negatively skewed distribution, 0.42 for the positively skewed distribution (both within 0.005 of the empirically obtained overall mean judgments). This effect of the skewing of the contextual distribution has been demonstrated for other hedonic dimensions, e.g., pleasantness of lemonades of varying sweetness, melodies of varying loudness, photographs of an actress simulating varying degrees of friendliness, and also for a variety of non-hedonic dimensions, e.g., size of squares, heaviness of lifted weights, largeness of abstract numerals. Applications to social planning and comparisons of life styles (e.g., Parducci, 1995, Chapters 12 and 13) are more speculative because of the difficulty of controlling the contexts experimentally.

## PLEASURE VERSUS UTILITY[1]

Returning to the judged pleasantness of winning different amounts of money, we should note that the total amount won was the same for both conditions of the demonstration experiment. Insofar as utility is linear to monetary values within this limited range of winnings, there seems little to choose between the two distributions. But consider the predicted effect of increasing the total winnings in the 1–21 condition by substituting 30 cents for one of the 21-cent trials: this extension of the upper endpoint of the context eliminates the skewing and thus reduces the mean judgment to 0.5 (i.e., to neutral, neither pleasant nor unpleasant). In this case, an increase in utility would have produced a decrease in pleasantness.

The simplest assumption would be that the effects of contextual skewing for hedonic judgments are absent for utility estimates. However, the lottery method for estimating utilities showed the usual skewing effects (Zaidel, 1971), and manipulation of contextual ranges can reverse the choices (Mellers and Cooke, 1994). In the absence of extensive research on the effects of contextual skewing upon choices, it seems intuitively likely that the effect would be much smaller for utilities.

Within any particular context, the order of pleasantness judgments must be the same as the order of utilities. It is when the context changes that these alternative measures yield profound differences. For example, in my computerized "Happiness Game" (Parducci, 1995, Chapter 8), players choose, on each trial, between different contexts (each context being the distribution of daily earnings of an imagined door-to-door salesman). The points earned by the player are proportional to the salesman's pleasures, as measured by range–frequency predictions from contextual skewing. Each context represents the salesman's distribution of earnings in a different neighborhood, with the game rigged so that the distributions are skewed more positively for the more profitable neighborhoods. The longer this game is played, the more likely players are to choose the more positively skewed contexts – so that the points they win actually decrease with increased experience at playing the game.

This kind of misapprehension seems characteristic of the profoundly sad paradox that maximizing utilities can sometimes minimize pleasures. We choose the job that pays more even when its likely hedonic context will be more positively skewed and thus yield less pleasure. A contemporary example is provided by the new PhDs, trained for research careers in academia, who flood onto Wall Street seeking jobs as investment bankers. If successful in this search, the hedonic contexts in which they experience pleasures and disappointments with their earnings may in many cases be positively skewed. The painful disappointments when they are earning less than their more successful colleagues will hardly be balanced by their occasionally triumphant investments.

[1]Although pleasure and utility are often confused, Kahneman and Varey (1991) present a cogent discussion of the conceptual differences.

**Table 1 | Frequency distribution of winnings.**

| Skewing | frequencies | | | | | | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Positive | | | | | | | 2 | 2 | 2 | 1 | | 1 | | | 1 | | | | 1 | | | | 1 | | | | 1 |
| Negative | 1 | | | | 1 | | | | 1 | | | | 1 | | | 1 | | 1 | 2 | 2 | 2 | | | | | | |
| Winnings | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 |

Real life is too complex to pin down contexts like this. However, we should at least consider the discouraging paradox that what we prefer may often afford less pleasure. One hears people complain that they are earning more but enjoying it less. By definition, we choose the alternative with higher utility. We may even tell ourselves that the consequences of our choice will average out to be more pleasant. But the contextual effects of skewing, unless they operate in the same way for utility as for pleasure, may often insure a preponderance of unpleasantness.

When distinguishing pleasure from utility, a deeper but less resolvable difference lies in what is experienced. No experienced sense of preference is crucial to the assessment of utility: the choice itself indicates the preference and hence the relative utility. However, it is difficult to assess the usual assumption that ratings of pleasantness indicate how much pleasure is actually experienced.

## REFERENCES


Kahneman, D., and Varey, C. (1991). "Notes on the psychology of utility," in *Interpersonal Comparisons of Well-Being*, eds J. Elster and J. E. Roemer (Cambridge: Cambridge University Press), 127–163.

Mellers, B. A., and Cooke, A. D. J. (1994). Tradeoffs depend on attribute range. *J. Exp. Psychol. Hum. Percept. Perform.* 20, 1055–1067.

Parducci, A. (1968). The relativism of absolute judgment. *Sci. Am.* 219, 84–90.

Parducci, A. (1995). *Happiness, Pleasure, and Judgment: The Contextual Theory and its Applications*. Mahwah, NJ: Erlbaum.

Zaidel, D. (1971). *A Judgmental Approach to Decision Analysis*. Dissertation abstracts international, 31, 10B (Ann Arbor, MI: University Microfilms No. 71-09,264).



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# Cognitive constraints on decision making under uncertainty

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## INTRODUCTION

Models of decision making under uncertainty should be grounded in general cognitive processes reflecting pervasive constraints from the nature of our environment. Developing integrated models applicable across different tasks provides converging constraints that increase the predictiveness of models to new situations.

Decision making is such a rich discipline that it is often considered in relative isolation, leading to entire fields devoted to specialized aspects and domains. Decision making under uncertainty can be better understood through the prism of general theories of cognition, constrained by representations and mechanisms developed to account for the much broader range of human activities (Anderson and Lebiere, 2003). This argument is an elaboration of Simon's bounded rationality (e.g., Simon, 1957) approach to constraining the rationality of optimal decision making by the cognitive limitations of the decision maker. Further, those cognitive limitations, and more generally the entire decision making process, should be modeled in a computational framework that captures in detail not only the cognitive mechanisms and representations involved (Newell, 1990) but also motivational processes (Kruglanski et al., 2007; Kruglanski and Gigerenzer, 2011) as well as perceptual (especially attentional) and motor processes (Card et al., 1983) to reflect the constraints of the task environment. Finally, decision making involves not simply raw cognitive processes but also knowledge and strategies on how to approach the problem (Gigerenzer et al., 1999). Fortunately, unified theories of cognition enable the representation of declarative and procedural knowledge constructs in a way that interacts with the constraints of the cognitive and perceptual processes to provide a rich account of performance in the task. Providing a detailed but unified computational account of those factors and their interaction across a wide range of tasks is essential for a deeper understanding of human decision making under uncertainty, as it involves general cognitive processes that are not limited to specific paradigms but take place across all human activities.

We illustrate those points by briefly describing a number of instances of our recent line of research in models of decision making. In particular, we want to highlight the importance of applying the same modeling approach to widely different paradigms of decision making (including domains that are not usually considered part of decision making) in order to bring the maximum force of converging constraints onto the problem. Indeed, the main issue with many decision making tasks is not that they are too difficult to model, but instead that too many distinct models provide roughly equivalent accounts of the data, making it hard to determine which provide a fundamental understanding of human decision making processes and which are merely well-fitted parametric descriptions of human performance.

## MODELS

Our initial model of decision making was applied to a task paradigm that is not traditionally considered part of decision making. Sequence-learning (e.g., Curran and Keele, 1993) usually involves speeded reaction tasks intended to investigate the impact of implicit learning processes on the detection of event sequences. In those tasks, a participant is exposed to a sequence of stimuli appearing in specific positions on a screen, and has to produce corresponding motor responses as quickly as possible. Given perceptual and motor limitations such as the need to shift visual attention to process a stimulus and to prepare a motor response before executing it, anticipating the location of the next stimulus and preparing the associated response allows for significantly faster reaction time. Learning in this task is measured by the improvement in response time between trial blocks in which the stimuli follow a repeated, deterministic sequence and those in which stimuli are randomly selected. Our sequence-learning model (Wallach and Lebiere, 2000; Lebiere and Wallach, 2001) works by building representations (chunks) of small pieces of the stimulus sequence in working memory, storing them in long-term memory and retrieving them by matching to the most recent stimuli to predict the next item in the sequence. Perceptual–motor factors play an important role in this task as well, as the ability to learn the sequence and effectively use anticipation fundamentally depends upon the length of the interval between a response and the next stimulus. The model reproduces numerous behavioral measures, including average response times, probability of errors and percentage of anticipatory actions. Constraining models using multiple performance dimensions is essential to reducing degrees of freedom, a common problem in simple decision making tasks.

The essential feature of this model is its use of memories for specific experiences. Different experiences compete to be retrieved for use through an activation calculus that is based on the rational analysis of cognition (Anderson, 1990; Anderson and Schooler, 1991) of how the availability of memories is determined by the statistical structure of the environment. This fundamental idea is that the mind makes micro-decisions in retrieving an experience on which to base its next action. This insight has played out in a series of subsequent applications of this model to tasks that similarly involves making a sequence of decisions and performing associated actions.

The approach was then applied to a classic multi-person game, paper rock scissors (PRS). Games constitute an excellent decision making testbed because of the natural competitive pressure to make the best possible decisions and maximize performance. PRS is a two-person game in which each player has to simultaneously select one of three options. The winner is determined by a circular relation between the three options, with no option intrinsically better than the others. Game theory prescribes random play as the optimal solution. However, while humans find it almost impossible to generate random actions, they find it quite natural to detect event sequences. Thus the sequence-learning approach is directly applicable to the iterated version of the game in which players engage in multiple rounds of play: the PRS model observes the opponent and learns small sequences of their moves in order to predict their next move, retrieves a best-matching sequence, and bases its move selection on that prediction. The model (Lebiere and West, 1999; West and Lebiere, 2001) matches quite well both aggregate level of human performance and specific characteristics such as the distribution of winning streaks. Its performance is also comparable to that of the best computer programs (Billings, 2000), an indication that cognitive constraints on decision making can provide useful functionality. The main aspect of this and other games for purposes of decision making is that the environment is not static but is instead another dynamic cognitive (human or model) entity adapting to one's actions, thus binding the players in a relation of reciprocal causation exhibiting signal detection characteristics such as stochastic resonance (West et al., 2005).

Sequential decision making is not confined to abstract games or experiments but instead is a natural component of many everyday situations. The game of baseball, specifically the competition between pitcher and batter, features the same structure of repeated choice among a set of possible actions. As in PRS, the pitcher has a number of options at his disposal varying in speed, location and movement, and, as in sequence-learning, because of perceptual–motor constraints the batter needs to anticipate the pitcher's choice in order to maximize the effectiveness of his response. Lebiere et al. (2003) applied the sequence-learning approach to two experimental situations. In the first one, pitch speed varied randomly between trials. The baseball model exploited the impact of recency in the base-level activation of the chunks representing each pitch to reflect the tendency of human batters to anticipate pitches similar to those they had seen recently. The fact that this pattern was observed in both humans and model despite the lack of any structure in the random trial-to-trial selection of pitch speed illustrates the pervasive nature of the biases inherited from the statistical structure of our environment. More fundamentally, it emphasizes that the concept of optimal decision making is relative to assumptions about the nature of the environment. For instance, probability matching, the common tendency to select choices in direct proportion to their quality, is often referred to as a suboptimal cognitive bias. However, that is only true if one assumes a fixed environment that one has adequately sampled. However, if one assumes a constantly changing environment, either independently or in response to our choices, probability matching can be an effective adaptive strategy to balance the need for constant sampling of the environment (exploration) with the goal to maximize performance given the currently available information (exploitation).

In the second experiment, pitch location was varied to reflect the current situation (specifically the balls and strikes count) to reflect strategic pitch selection in actual baseball games. The model's sensitivity to the context closely matched the strategic adaptivity of human batters. In both cases, the cognitive biases and mechanisms built into the architecture matched the human data *a priori* at least as well as a Hidden Markov model that had been trained on part of the data and could predict the rest *a posteriori*, emphasizing the role that cognitive constraints can play in modeling decision making biases in a principled, general basis rather than developing and parameterizing *ad hoc*, task-specific, models.

To demonstrate the relevance of the model to classical decision making paradigms and the power of cognitive constraints to *a priori* predict performance, Stewart et al. (2009) submitted a version of the PRS model to a choice prediction competition. The choice model uses the blending mechanism (Lebiere, 1999) to generate continuous expectations of the outcome of each option, reflecting both their payoffs and probabilities. The model won the part of the competition in which decisions between safe and risky options were based on prior experience with those options (Erev et al., 2010). Particularly remarkable is the fact that the sequence-learning model matched human performance better than models that attempted to learn the value of each option in isolation despite, as in the first baseball experiment, the lack of any sequential structure in the task. But while the recency effect seems to be a pervasive bias ingrained in human cognition, not all such cognitive biases are equally stable and permanent. Lebiere et al. (2007) showed how the very same recency effect in the activation of experiences, weighted against a longer-term frequency effect, can explain the appearance and then disappearance of risk aversion bias in deciding between safe and risky choices. The recency effect initially dominates and leads selection away from risky choices, but the frequency effect then restores over time the balance between safe and risky options. This account is directly compatible with other sampling-based explanations (e.g., Denrell and Le Mens, 2007; Le Mens and Denrell, 2011) but provides precise predictions of the time course of the learning and unlearning of the risk aversion bias as a function of experience.

The direct implication of our account of decision making under uncertainty is the lack of stable risk preferences. Instead, the model attempts to achieve the best possible performance under cognitive and task constraints (such as payoff function and other performance metrics) without explicitly considering second-order information such as the amount of risk present in their decisions. In addition to the impact of learning and experience, cognitive factors influencing the level of risk assumed include individual differences parameters such as working memory capacity (Rehling et al., 2004) and noise in memory retrieval (West and Lebiere, 2001) as well as information framing effects (Martin et al., 2011).

## CONCLUSION

The application of the same model across a wide range of paradigms, from implicit learning of sequences to multi-person games in abstract and embodied settings to classical decision making tasks illustrates the predictive benefits of models based on cognitive architectures. Specifically, the cognitive constraints embedded in the architecture interact with the heuristic strategies used and the task environments to account for a broad pattern of results across multiple fields with limited parameter variations.

However, work remains to be done to achieve true unification. Instantiations of the model across paradigms still require the modeler to implement representation choices that reflect the nature of the task. A key part of decision making involves not only applying given heuristics and strategies, but also the metacognitive task of selecting among them and adopting the proper representation to implement them. Only when that aspect of decision making is viewed as an integral part of decision making and incorporated in models will a true theory of the field be achieved.

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## REFERENCES

Anderson, J. R. (1990). *The Adaptive Character of Thought*. Hillsdale, NJ: Erlbaum.

Anderson, J. R., and Lebiere, C. (2003). The Newell test for a theory of cognition. *Behav. Brain Sci.* 26, 587–637.

Anderson, J. R., and Schooler, L. J. (1991). Reflections of the environment in memory. *Psychol. Sci.* 2, 396–408.

Billings, D. (2000). The first international RoShamBo programming competition. *ICGA J.* 23, 42–50.

Card, S. K., Moran, T. P., and Newell, A. (1983). *The Psychology of Human Computer Interaction*. Hillsdale, NJ: Lawrence Erlbaum.

Curran, T., and Keele, S. W. (1993). Attentional and nonattentional forms of sequence learning. *J. Exp. Psychol. Learn. Mem. Cogn.* 19, 189–202.

Denrell, J., and Le Mens, G. (2007). Interdependent sampling and social influence. *Psychol. Rev.* 114, 398–422.

Erev, I., Ert, E., Roth, A. E., Haruvy, E., Herzog, S., Hau, R., Hertwig, R., Stewart, T., West, R., and Lebiere, C. (2010). A choice prediction competition, for choices from experience and from description. *J. Behav. Decis. Mak.* 23, 15–47.

Gigerenzer, G., Todd, P. M., and the ABC Group. (1999). *Simple Heuristics that Make us Smart*. New York: Oxford University Press.

Kruglanski, A. W., and Gigerenzer, G. (2011). Intuitive and deliberate judgments are based on common principles. *Psychol. Rev.* 118, 97–109.

Kruglanski, A. W., Pierro, A., Mannetti, L., Erb, H., and Chun, W. Y. (2007). "On the parameters of human judgment," in *Advances in Experimental Social Psychology*, Vol. 39, ed. M. P. Zanna (San Diego, CA: Zanna Elsevier Academic Press), 255–303.

Le Mens, G., and Denrell, J. (2011). Rational learning and information sampling: on the 'naivety' assumption in sampling explanations of judgment biases. *Psychol. Rev.* 118, 379–392.

Lebiere, C. (1999). The dynamics of cognitive arithmetic. Kognitionswissenschaft special issue on cognitive modelling and cognitive architectures, D. Wallach and H. A. Simon (eds). *J. German Cogn. Sci. Soc.* 8, 5–19.

Lebiere, C., Gonzalez, C., and Martin, M. (2007). "Instance-based decision-making model of repeated binary choice," in *Proceedings of the Eighth International Conference on Cognitive Modeling*, Ann Arbor, MI.

Lebiere, C., Gray, R., Salvucci, D., and West, R. (2003). "Choice and learning under uncertainty: a case study in baseball batting," in *Proceedings of the Twenty-fifth Annual Meeting of the Cognitive Science Society*, Boston, MA, 704–709.

Lebiere, C., and Wallach, D. (2001). "Sequence learning in the ACT-R cognitive architecture: Empirical analysis of a hybrid model," in *Sequence Learning: Paradigms, Algorithms, and Applications*, eds R. Sun and L. Giles (Germany: Springer LNCS/LNAI), 188–212.

Lebiere, C., and West, R. L. (1999). "A dynamic ACT-R model of simple games," in *Proceedings of the Twenty-first Conference of the Cognitive Science Society* (Mahwah, NJ: Erlbaum), 296–301.

Martin, J. M., Juvina, I., Lebiere, C., and Gonzalez, C. (2011). "The effects of individual and context on aggression in repeated social interaction," in *Proceedings of the HCI International 2011 Conference, HCII 2011*, Orlando, FL.

Newell, A. (1990). *Unified Theories of Cognition*. Cambridge, MA: Harvard University Press.

Rehling, J., Lovett, M., Lebiere, C., Reder, L. M., and Demiral, B. (2004). "Modeling complex tasks: an individual difference approach," in *Proceedings of the 26th Annual Conference of the Cognitive Science Society*, August 4–7, Chicago, 1137–1142.

Simon, H. (1957). "A behavioral model of rational choice," in *Models of Man, Social and Rational: Mathematical Essays on Rational Human Behavior in a Social Setting*. New York: Wiley.

Stewart, T. C., West, R., and Lebiere, C. (2009). "Applying cognitive architectures to decision making: how cognitive theory and the equivalence measure triumphed in the technion prediction tournament," in *Proceedings of the Thirty-First Cognitive Science Conference*, Amsterdam.

Wallach, D., and Lebiere, C. (2000). "Learning of event sequences: an architectural approach," in *Proceedings of International Conference on Cognitive Modeling 2000* (NL: Universal Press), 271–279.

West, R. L., and Lebiere, C. (2001). Simple games as dynamic, coupled systems: Randomness and other emergent properties. *J. Cogn. Syst. Res.* 1, 221–239.

West, R. L., Stewart, T. C., Lebiere, C., and Chandrasekharan, S. (2005). "Stochastic resonance in human cognition: ACT-R vs. game theory, associative neural networks, recursive neural networks, q-learning, and humans," in *Proceedings of the 27th Annual Conference of the Cognitive Science Society*, eds B. Bara, L. Barsalou and M. Bucciarelli (Mahwah, NJ: Lawrence Erlbaum Associates), 2353–2358.

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# Unstable values in lifesaving decisions

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## INTRODUCTION

Classical economic approaches to the study of preferences and risky choices assume that human preferences are stable and rational. However, subsequent empirical research has demonstrated that preferences are often constructed and that choices are influenced by a variety of factors that frequently deviate from normative decision-making models. While many of these studies have confirmed that preferences depend on presentation formats, response modes, processing modes, mood states, attitudes, and a host of other moderators (e.g., Lichtenstein and Slovic, 2006), it should be noted that preferences are also a manifestation of a decision-maker's inherent values. While core values are often seen as relatively stable (Malle and Dickert, 2007), tradeoffs among those values are often ill-defined, setting the stage for preference reversals induced by contextual factors that should not really matter (Lichtenstein and Slovic, 2006). But how do values shape our preferences and guide our decisions? In the present article we conceptualize preferences as manifestations of feelings and values, and briefly describe how they influence behavior in certain situations involving risk.

Specifically, we aim to show how values can manifest themselves as preferences and influence choices in situations where people make decisions about others whose lives are at risk. Touching on issues relevant for risk perception and risk management as well as the underlying processes of valuations that lead to preferences, we go beyond the common conceptualization of risky choices represented as outcomes with well-defined probabilities. Instead, our research focuses on and documents people's inconsistent use of values when making decisions about whether or not to aid other people whose lives are endangered.

In our culture, most people would endorse a normative model asserting that every human life is intrinsically equal in value. This implies a linear relationship between the number of people at risk and the amount of money one should be willing to contribute in order to reduce or eliminate that risk. However, studies of actual behavior show that, descriptively, this is hardly ever the case (e.g., Slovic, 2007). On the contrary, as the number of people at risk increases, the marginal rate of contributions decreases, revealing a general insensitivity to large losses of life (Fetherstonhaugh et al., 1997). In many cases, valuations are actually highest for a single individual life and decrease when more lives are at risk (Kogut and Ritov, 2005; Small et al., 2007). In our research, we examine the underlying mechanisms that can explain some of the deviations between normative and descriptive models of helping behavior. In the remainder of this article, we highlight the role that affect plays in the construction of preferences for valuing the life of someone at risk and focus on some of the affective mechanisms we believe to be central to lifesaving decisions.

## THE ROLE OF AFFECT AND AFFECT REGULATION IN VALUATIONS OF PEOPLE AT RISK

Decisions in situations of risk are strongly influenced by affective and emotional responses of the decisionmaker (Loewenstein et al., 2001). People often evaluate the risks, risk factors, and potential benefits on an affective dimension (Slovic et al., 2002). Charitable giving (as one expression of valuing other people's lives) is likewise heavily influenced by our emotions (Andreoni, 1990; Batson, 1990; Slovic, 2007). In these situations, affective responses serve both as a way to inform the decisionmaker about the value they should place on other people at risk as well as constitute a source of motivation underlying helping. In our research we have found that the motivating emotions vary in different stages of the valuation process (Dickert et al., 2011b). We show that valuations are constructed based on affective responses and follow a specific time-course that we model with two separate stages. According to this model, when confronted with the need to help someone at risk, people first consider how they feel about themselves to determine whether they will help or not (Stage 1). If they decide to help, people then determine the amount of help that they want to provide by consulting their feelings regarding the persons at risk (Stage 2). Thus, the decision to donate or not is primarily determined by affective responses that are focused on the self (e.g., how much better a person feels after helping someone else) and the amount donated is primarily determined by emotions that are focused on others (e.g., sympathy and compassion).

As is evident from this distinction, behavioral responses in the face of risk are not only affected by our feelings, but also exert an influence on them. Self-focused feelings may provide the basis for helping responses, but people also feel better about themselves after helping (Dickert et al., 2011c; Dunn et al., 2008). As such, emotion regulation and mood-management strategies become a critical component in valuations of people at risk. Similarly, emotion regulation also comes into play for other-focused emotions, as documented by the breakdown of compassion when we are confronted with large populations at risk (Slovic, 2010a). In order to better understand the role of affect (and affect regulation) in valuations and determine when feelings lead to an inconsistent use of values underlying choices, it is necessary to take a closer look at the processes that lead to the generation of feelings.

## FACTORS INFLUENCING THE GENERATION OF AFFECTIVE RESPONSES IN SITUATIONS OF RISK

It is important to note that valuations of people at risk (and the underlying affective processes) are similar to other preferences in the sense that they are context-dependent. The way the risk is portrayed (e.g., by different framing or presentation formats) greatly influences affective responses underlying these valuations. In our research we have given special considerations to processes related to (1) mental imagery, (2) individual differences, and (3) attention.

## MENTAL IMAGERY

Mental images are intimately related to emotional reactions. This is especially true for mental images that underlie risk perceptions (Slovic, 2010a). The more vividly people in need are described the more likely we are to respond affectively and generate feelings underlying the valuation of their lives. Presentation formats that enhance mental imagery (e.g., showing the faces of people at risk and using information-processing modes that facilitate clearer and more concrete mental representations) increase affective responses (Dickert et al., 2011a). Conversely, depicting people abstractly (e.g., as statistical lives rather than identified human beings) decreases affective responses and subsequent valuations (Small et al., 2007). In situations where a large group of people is at risk, it is likely that mental images are less concrete and emotional responses less pronounced. Research has demonstrated that mental images (and the resulting cognitive and emotional processes) are different for individuals than for groups (Hamilton and Sherman, 1996). It is easier to imagine a single person at risk than a group of persons. This causes affective responses to be strongest for a single individual and considerably weaker as the number of people at risk increases (Kogut and Ritov, 2005), resulting in the nonrational reaction where "the more who die, the less we care" (Slovic, 2010b).

## INDIVIDUAL DIFFERENCES

People differ in their values and attitudes toward risk (for themselves and others) as well as in their propensity to engage in information-processing that facilitates affective responses to risk. Generally more pro-social value orientations are related to feeling more distress and greater motivation to act in ways that are beneficial to others (Van Lange et al., 2007). Similarly, differences in affective reactivity, mental imagery, and information-processing styles play a role in the generation of feelings that underlie responses to risk. In our studies we have found evidence that differences in numerical ability together with variations in presentation format change the perception of risk for others (Dickert et al., 2011a). A consistent finding of these studies is that the concreteness and use of mental imagery in valuations of people at risk is moderated by the numerical ability of the perceiver. Lower numerical ability leads people to construct clearer mental representations and base their valuations on them, whereas people with higher numerical ability have more abstract mental representations that are not related to their valuations.

Another demonstration of how individual differences influence affective responses and valuations of people at risk comes from Kogut (2011), who has shown that people with a strong belief in a just world (i.e., those who believe the world is a just place) are more likely to blame others for their predicament and are less willing to provide help. Thus, their risk perception is prominently influenced by their general attitude toward blame and responsibility. More importantly, however, Kogut (2011) argues that these general attitudes influence valuations of lives particularly when the people at risk are depicted in a way that facilitates clearer mental images and stronger emotional responses (i.e., when they are identified).

## ATTENTION

An additional precursor to the generation of feelings is the ability to focus one's attention on the people at risk. In line with the effects of mental imagery, this is usually easier for a single individual at risk rather than a group of people (Hamilton and Sherman, 1996). In our research we have found that presenting similar individuals at risk as part of a group reduces affective responses to any single one of them (Dickert and Slovic, 2009). Furthermore, affective responses such as sympathy toward a starving child decreased when the face of the child disappeared from view. The nature of affective responses appears to be stronger when triggered by something immediate rather than reconstructed from memory. These results highlight the degree to which simple fluctuations in our attention can influence our feelings and thus our values. This helps explain why our responses toward opportunities to aid people whose lives are endangered are unstable and often inconsistent with normative principles that we nonetheless strongly endorse.

## SUMMARY

Although preferences and their underlying values are assumed to be stable by classical economic theory, empirical research has often shown deviations from normative principles and documented how preferences under risk are constructed and even shaped by seemingly irrelevant factors. What is remarkable about the construction of preference is its ubiquitous presence in nearly every decision-making domain. In accord with this idea, we argue that values (and valuations) can also be constructed and are therefore unstable. This is particularly evident in situations where valuations depend on affective responses (e.g., valuations of other people at risk). The research documenting mental imagery and attention as underlying processes of affective responses and research showing individual differences as moderators of these processes help explain why we do not hold stable values for saving human lives. Descriptive models show that our responses to people at risk are not always rational nor immune from biases common to other forms of preference. We suggest that the processes leading up to inconsistencies in valuations are strongly related to affect and affect regulation strategies. While most of us would probably agree that every life should be valued highly, our behaviors toward people in danger are often inconsistent with this belief.

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## REFERENCES

Andreoni, J. (1990). Impure altruism and donations to public goods: a theory of warm-glow giving. *Econ. J.* 100, 464–477.

Batson, C. D. (1990). How social an animal? The human capacity for caring. *Am. Psychol.* 45, 336–346.

Dickert, S., Kleber, J., Peters, E., and Slovic, P. (2011a). Numeric ability as a precursor to pro-social behaviour: the impact of presentation format on the cognitive mechanisms underlying donation decisions. *Judgm. Decis. Mak.* 6, 638–650.

Dickert, S., Sagara, N., and Slovic, P. (2011b). Affective motivations to help others: a two-stage model of donation decisions. *J. Behav. Decis. Mak.* 4, 297–306.

Dickert, S., and Slovic, P. (2009). Attentional mechanisms in the generation of sympathy. *Judgm. Decis. Mak.* 4, 297–306.

Dickert, S., Västfjäll, D., and Slovic, P. (2011c). Emotionally difficult pro-social choices: the role of dissonance reduction in donation decisions. Manuscript submitted for publication.

Dunn, E., Aknin, L., and Norton, M. (2008). Spending money on others promotes happiness. *Science* 319, 1687–1688.

Fetherstonhaugh, D., Slovic, P., Johnson, S. M., and Friedrich, J. (1997). Insensitivity to the value of human life: a study of psychophysical numbing. *J. Risk Uncertain.* 14, 283–300.

Hamilton, D. L., and Sherman, S. J. (1996). Perceiving persons and groups. *Psychol. Rev.* 103, 336–355.

Kogut, T. (2011). Someone to blame: when identifying a victim decreases helping. *J. Exp. Soc. Psychol.* 47, 748–755.

Kogut, T., and Ritov, I. (2005). The "identified victim" effect: an identified group, or just a single individual? *J. Behav. Decis. Mak.* 18, 157–167.

Lichtenstein, S., and Slovic, P. (2006). *The Construction of Preference*. New York: Cambridge University Press.

Loewenstein, G., Weber, E. U., Hsee, C. K., and Welch, N. (2001). Risk as feelings. *Psychol. Bull.* 127, 267–286.

Malle, B. F., and Dickert, S. (2007). "Values," in *The Encyclopedia of Social Psychology*, eds R. Baumeister and K. Vohs (Thousand Oaks, CA: Sage), 1011–1014.

Slovic, P. (2007). "If I look at the mass I will never act": psychic numbing and genocide. *Judgm. Decis. Mak.* 2, 79–95.

Slovic, P. (2010a). *The Feeling of Risk: New Perspectives on Risk Perception*. London: Earthscan.

Slovic, P. (2010b). "The more who die, the less we care," in *The Irrational Economist: Making Decisions in a Dangerous World*, eds E. Michel-Kerjan and P. Slovic (New York: Public Affairs), 30–40.

Slovic, P., Finucane, M. L., Peters, E., and MacGregor, D. G. (2002). "The affect heuristic," in *Heuristics and Biases: The Psychology of Intuitive Judgment*, eds T. Gilovich, D. Griffin, and D. Kahneman (New York: Cambridge University Press), 397–420.

Small, D. A., Loewenstein, G., and Slovic, P. (2007). Sympathy and callousness: the impact of deliberative thought on donations to identifiable and statistical victims. *Organ. Behav. Hum. Decis. Process.* 102, 143–153.

Van Lange, P. A. M., Bekkers, R., Schuyt, T. N. M., and Van Vugt, M. (2007). From games to giving: social value orientation predicts donations to noble causes. *Basic Appl. Soc. Psych.* 29, 375–384.

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# Role of emotion in shifting choice preference: a neuroscientific perspective

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What role(s) do emotions have in choice preference? Individuals' choices depend on their memories and cognition but also on their current emotional state. Emotions can play a necessary functional role in decision-making, but in doing this, emotions can alter the stability of the process. The argument for a necessary functional role of emotions is supported by converging evidence from neuropsychological patients with impairments in either emotional responding or in decision-making, alongside human brain imaging. We also point out that functional brain imaging studies need to target brain areas responding to emotion in order to provide stronger evidence for emotion specifically modulating the process of decision-making to influence choice preference.

## NEUROPSYCHOLOGICAL AND fMRI STUDIES OF THE vmPFC AND OTHER BRAIN REGIONS

Neuropsychological studies have shown that patients with damage to ventromedial prefrontal cortex (vmPFC) brain regions display flattened emotions, an inability to respond to emotional events, and less responsiveness to punishment (Fellows and Farah, 2005; Naqvi et al., 2006). In addition, patients with vmPFC lesions show impaired decision-making. It has been argued that this impaired decision-making reflects altered emotional reactivity. The "somatic marker hypothesis" proposes that in situations where choices could bring either positive reward or negative outcomes and losses, decision-making is modulated by the ability to recruit emotional feedback from past events (Bechara et al., 1994). The Iowa gambling task (IGT; Anderson et al., 1999) has been used to test this hypothesis and examine the phenomena of poor decision-making in patients with damage to prefrontal cortex. Players must select a card from one of four decks. Each card leads to winning or losing money. Unknown to the player, some decks contain cards with higher gains and losses, which if repeatedly selected will lead to an overall loss. Over the course of multiple trials, typical players begin to avoid these high risk decks. Patients, on the other hand, were found to be unable to forgo immediate gains for long-term reward to win the game. The results also showed that patients with vmPFC damage, unlike healthy controls, did not produce skin-conductance responses (SCRs), a physiological measure of emotional responsiveness, before making choices that had negative outcomes. The vmPFC may therefore be necessary for the emotional evaluation of future choices. Interestingly, patients with amygdala damage were also found to perform poorly on the gambling task (Bechara et al., 1999; Weller et al., 2007). However, unlike vmPFC patients, amygdala patients not only failed to emotionally react in anticipation of a negative choice, but failed to produce SCRs after negative decision outcomes. This suggests that the amygdala is part of a feedback circuit that evaluates the emotional outcome of choices, modulating prefrontal regions. Emotional associations can thus bias choice preference. Note that the emotional state of the participant in these paradigms can change rapidly across trials, and the data suggest that this modulates decision-making. Emotional modulation of decision-making can make human choice contextually dependent, but this is at the cost of stability in decision-making, across different emotional contexts.

These results contrast with at least some of the results from functional magnetic resonance imaging (fMRI) studies, for instance Lawrence et al. (2009) carried out an fMRI study of healthy control participants performing the IGT. The blood-oxygenation-level dependent (BOLD) contrast was accessed across specific time periods within each choice trial. The BOLD signal (based on blood flow) is proportional to neural activity. Comparing activity at the point where participants found out the outcome of their decision (i.e., when a reward or punishment from making a choice was shown) revealed more activity in the caudate, nucleus accumbens, insula, and thalamus for choices which yielded a reward (winning money) compared to responses which resulted in punishment (losing money). They also compared activity between trials where participants had to actively choose a card to those where participants had to select specified card decks. Regions of the vmPFC, implicated in the neuropsychological studies were more active for decision-making trials than for control trials. More specifically, higher BOLD activity was reported in bilateral areas of the medial orbitofrontal cortex (BA 11), as well as in regions of the ventral anterior cingulate cortex (BA 24 and 32), extending to the caudate. In addition, when making choices that would lead to overall losses of money in the task, neural activity was found in the orbital frontal cortex and insula. Other fMRI studies using the IGT have found similar activity in the medial frontal gyrus (BA 10; Fukui et al., 2005; Windmann et al., 2006). These results point to a role of orbito- and medial-frontal cortex in relation to positive and negative aspects of reward in the IGT, but they do not necessarily demonstrate the involvement of emotion-based influences on decision-making as opposed to other aspects of the evaluation process. Indeed, other research suggest that key neural regions that form part of the neural circuitry for emotional responding, namely the amygdala and hippocampus, are not involved during the task (Li et al., 2010).

To assess whether there is a more specific role of emotion in the IGT, we have recently assessed activity in brain regions specifically associated with positive and negative emotional responses. Participants viewed pre-categorized images from the International Affective Picture System (IAPS; Lang et al., 1997) conveying positive, negative, and neutral valence. Regions found to be more activated by positive than negative emotion, and vice versa, were then used as regions of interest for the analysis of brain activity during the IGT. A comparison was carried out on the percentage of change in BOLD signal between individuals who learned the task (who selected more cards from advantageous card decks) and non-learners (who selected more cards from disadvantageous card decks). Example data from the region specific to positive emotion in the time period in response to choice outcome are presented in **Figure 1**.

The region of interest analysis revealed that activation in the left temporal pole varied as a function of the type of reinforcement (i.e., positive or negative outcome). Other results suggest that the left temporal pole is a crucial part of the neural network involved in emotional reactivity (Lee et al., 2004; Britton et al., 2006). Thus, the results indicate that a critical brain area involved in emotional responding (the left temporal pole), and independently defined in relation to emotional stimuli, was differentially activated in the IGT. While supporting the case for emotion-based modulation of decision-making in the IGT, we note also that there was no evidence for differential activation of the vmPFC, though this was activated in our emotional localizer task (the IAPS). Hence, it remains unclear whether any involvement of the vmPFC in the IGT reflects emotion-based responding or other aspects of decision-making. Irrespective of this, the results indicate that brain areas involved in emotion are significantly active during decision-making, and provide a context for temporary instability when decisions are made. To evaluate whether this context plays a causal role in decision-making, though, requires that further steps are taken, which we consider below.

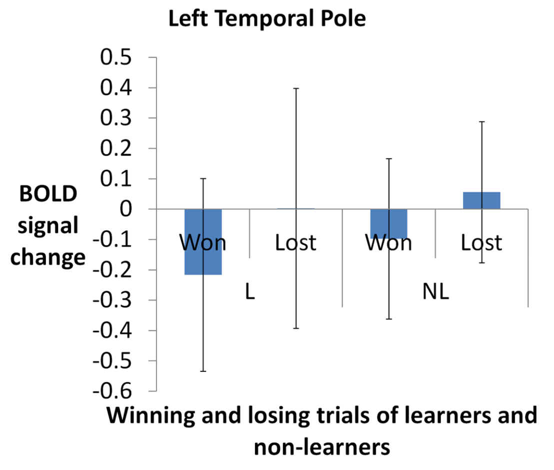


**FIGURE 1 | Blood-oxygenation-level dependent signal change for winning- and losing-trials in the left temporal pole (a region specific to positive emotions i.e., positive minus neutral contrast of IAPS picture rating task.** L, learners (who chose from advantageous card decks more frequently). NL, non-learners. Activity was higher for the winning trials, $F(3,57) = 7.562$, $p < 0.001$. Error bars denote SD of the group.

## APATHY AND ASSOCIATED BRAIN MECHANISMS

Understanding the role of emotion in decision-making that is influence by current emotional state on a moment to moment basis, strongly effecting stability of choice has important clinical implications. Apathy is a disorder of diminished motivation that affects every day adaptive behavior (Marin et al., 1994). Clinical studies have found that motivational loss as a result of apathy affects quality of life by (amongst other things) reducing social interactions (Resnick et al., 1998; Reid-Arndt et al., 2007).

Njomboro (2009) examined the performance of brain-injured patients either with or without symptoms of apathy. Apathetic patients showed reduced effects of reward in the IGT, and were neither strongly affected by high reward values in the initial stages of the task nor by longer-term reward outcomes as the task progressed. The results suggest that lowered emotional responding, found in apathetic patients, can have a direct effect on the reward-mediated decision-making. Emotion mediates the effects of a reward, influencing individual's choices, however this pathway may not be present in these patients.

Clinical studies have investigated the roles that neural structures and circuits play in bringing about and maintaining a motivational state, which if affected, results in less goal-directed behavior (Brown and Pluck, 2000; Marin and Wilkosz, 2005). The anterior cingulum, nucleus accumbens, ventral pallidum, thalamus, and the ventral tegmental area form the core of the neural system recruited for motivation, and the nucleus accumbens, ventral pallidum, and thalamus have been suggested to modulate motivation (Marin and Wilkosz, 2005). Marin (1996) posits that apathy emerges when there is damage to this circuitry. Similar neural networks including neural areas such as the anterior cingulate and nucleus accumbens are also related to performance on the IGT. The basal ganglia has also been reported to be involved in conveying motivational signals to and from the frontal cortex (van Reekum et al., 2005) for decision-making. Damage of the basal ganglia may be critical for apathy and may lead to impaired performance in the IGT. A clear future direction for research is to assess the role of different brain regions affected in a wide variety of disorders where apathetic symptoms may occur (e.g., in Parkinson's disease in relation to the basal ganglia), to test for a modulating role on decision-making which has implications on the stability of choice preference.

Functional magnetic resonance imaging has revealed the involvement of vmPFC and subcortical regions in decision-making. This is informative about the neural areas affected in motivational disorders that have been postulated to involve similar neural networks. Further studies that combine neuropsychological analyses with functional brain imaging should provide evidence not only that damage to brain regions dealing with emotional responding can alter neural activity in decision-making, but also that emotional change acts as a mediator of choice preference. Any mediating effect of emotion will change the stability of decision-making, making choice preference both more labile and more flexible than would be the case if decisions were purely cognitive in nature.

## REFERENCES

Anderson, S. W., Bechara, A., Damasio, H., Tranel, D., and Damasio, A. R. (1999). Impairment of social and moral behaviour related to early damage in the human prefrontal cortex. *Nat. Neurosci.* 2, 1032–1037.

Bechara, A., Damasio, A. R., Damasio, H., and Anderson, S. W. (1994). Insensitivity to future consequences following damage to human prefrontal cortex. *Cognition* 50, 7–15.

Bechara, A., Damasio, H., Damasio, A. R., and Lee, G. P. (1999). Different contributions of the human amygdala and ventromedial prefrontal cortex to decision-making. *J. Neurosci.* 19, 5473–5481.

Britton, J. C., Taylor, S. F., Sudheimer, K. D., and Liberzon, I. (2006). Facial expressions and complex IAPS pictures: common and differential networks. *Neuroimage* 31, 906–916.

Brown, R. G., and Pluck, G. (2000). Negative symptoms: the 'pathology' of motivation and goal-directed behaviour. *Trends Neurosci.* 23, 412–417.

Fellows, L. K., and Farah, M. J. (2005). Dissociable elements of human foresight: a role for the ventromedial frontal lobes in framing the future, but not in discounting future rewards. *Neuropsychologia* 43, 1214–1221.

Fukui, H., Murai, T., Fukuyama, H., Hayashi, T., and Hanakawa, T. (2005). Functional activity related to risk anticipation during performance of the Iowa gambling task. *Neuroimage* 24, 253–259.

Lang, P. J., Bradley, M. M., and Cuthbert, B. N. (1997). *International Affective Picture System (IAPS): Technical Manual and Affective Ratings*. Gainesville: NIMH Center for the Study of Emotion and Attention.

Lawrence, N. S., Jollant, F., O'Daly, O., Zelaya, F., and Phillips, M. L. (2009). Distinct roles of prefrontal cortical subregions in the Iowa gambling task. *Cereb. Cortex* 19, 1134–1143.

Lee, G. P., Meador, K. J., Loring, D. W., Allison, J. D., Brown, W. S., Paul, L. K., Pillai, J. J., and Lavin, T. B. (2004). Neural substrates of emotion as revealed by functional magnetic resonance imaging. *Cogn. Behav. Neurol.* 17, 9–17.

Li, X., Lu, Z.-L., D'Argembeau, A., Ng, M., and Bechara, A. (2010). The Iowa gambling task in fMRI images. *Hum. Brain Mapp.* 31, 410–423.

Marin, R. S. (1996). "Apathy and related disorders of diminished motivation," in *Review of Psychiatry, Section II: Neuropsychiatry for Clinicians*, eds L. J. Dickstein, M. B. Riba, and J. M. Oldham (Washington DC: American Psychiatric Press), 205–242.

Marin, R. S., Firinciogullari, M. S., and Biedrzycki, R. C. (1994). Group differences in the relationship between apathy and depression. *J. Nerv. Ment. Dis.* 182, 235–239.

Marin, R. S., and Wilkosz, P. A. (2005). Disorders of diminished motivation. *J. Head Trauma Rehabil.* 20, 377–388.

Naqvi, N., Shiv, B., and Bechara, A. (2006). The role of emotion in decision making; a cognitive neuroscience perspective. *Curr. Dir. Psychol. Sci.* 15, 260–264.

Njomboro, P. (2009). *The Neuropsychiatry of Apathy*. Ph. D. Thesis, University of Birmingham, UK.

Reid-Arndt, S. A., Nehl, C., and Hinkebein, J. (2007). The frontal systems behaviour scale (FrSBe) as a predictor of community integration following a traumatic brain injury. *Br. Inj.* 21, 1361–1369.

Resnick, B., Zimmerman, S. I., Magaziner, J., and Adelman, A. (1998). Use of the apathy evaluation scale as a measure of motivation in elderly people. *Rehabil. Nurs.* 23, 141–147.

van Reekum, R., Stuss, D. T., and Ostrander, L. (2005). Apathy: why care? *J. Neuropsychiatry Clin. Neurosci.* 17, 7–19.

Weller, J. A., Levin, I. P., Shiv, B., and Bechara, A. (2007). Neural correlates of adaptive decision-making for risky gains and losses. *Psychol. Sci.* 18, 958–964.

Windmann, S., Kirsch, P., Meir, D., Stark, R., Walter, B., Gunturkun, O., and Vaitl, D. (2006). On framing effects in decision-making: linking lateral versus medial orbitofrontal cortex activation to choice outcome processing. *J. Cogn. Neurosci.* 18, 1198–1211.



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# Risk attitude, investments, and the taste for luxuries versus necessities

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## 1. INTRODUCTION

Individuals should differ in their tolerance for risky financial investments. For one thing, people face different income streams. A freelance writer typically faces considerable variability in income, and long-term unpredictability. These should generally be compensated by less risky investment. But a tenured professor faces little variability or unpredictability and can thus afford to take more risks elsewhere, other things being equal. For another thing, people have different tastes for expenditures. Some people value the "finer things" that money can buy, while others are convinced that the best things in life are free.

Individual differences in the taste for luxury should thus affect the utility function for money, e.g., income in retirement. Such differences can provide a test of methods for assessing the utility function. Those with no particular interest in luxuries should have a concave utility function: a reasonable amount of money is sufficient and much more will not improve life that much. Those with more interest in luxuries should have utility functions closer to linear. The former should be more risk averse in investing, other things being equal, in line with expected-utility theory.

I have argued that we should think of utility as something real in the sense in which time and longitude are real, i.e., a measure based on a conception that we superimpose on the world (Baron, 2008), yet the same thing regardless of how we measure it. Utility is not just the output of a black box, such as the answer that subjects give to questions about hypothetical monetary gambles. Such answers could be wrong, just as sundials are wrong about time and bad chronometers lead to errors in assessing longitude. Yet, investment advisors often use hypothetical gambles to provide advice about saving for retirement.

Measures of risk attitude based on gambles are influenced by many other factors aside from the utility of money (Schoemaker, 1993; Baron, 2008). For example, decisions about risks are affected by: general beliefs about risk taking as a character trait, such as a desire to avoid being foolhardy, or timid; personality traits such as impulsiveness, anxiety level, and sensation-seeking; social pressures connected with these beliefs; superstition; anticipation of emotional reactions to losses, such as regret, guilt feelings (if others are affected), and disappointment, which go beyond the financial consequences in terms of lost purchasing power; lack of understanding of comparative risks and benefits, or the risk/benefit trade-off; misperceptions of probability, such as neglect or exaggeration of very low probabilities; and isolation of individual decisions, so that they are not seen in the context of a total portfolio of income streams from various sources. Moreover, hypothetical gambles provide results that are internally inconsistent (Baron, 1997). More direct measures of utility, such as those based on comparison of differences, may be more valid, and they are at least as justifiable on theoretical grounds (Krantz et al., 1971; Baron, 2008, Chapter 4).

I report a small study suggesting that difference-based measures are more sensitive than gamble-based measures to the taste for luxuries. My approach was to ask people to evaluate a sample of possible expenditures, which I then place, *post hoc*, along a continuum from necessities to luxuries.

## 2. METHOD

Subjects were 77 members of a panel who did studies on the World Wide Web for pay. (Four others were omitted because they did the study too quickly to have read carefully.) Ages ranged from 20 to 76 (median 44); 36% were male.

The study began with 36 pages about expenditures after retirement (defined as no longer working or reaching age 65, whichever came last). Examples of the expenditures were:

owning one inexpensive car (versus no car);
owning a second inexpensive car (versus one inexpensive car);
owning two top-of-the line cars (versus two inexpensive cars);
having an extra bedroom in your home, for visitors;
having an extra two bedrooms in your home, for visitors, as opposed to one;
flying to see relatives (including children) or friends once a year;
flying to see relatives (including children) or friends five times per year (as opposed to once);
hiring someone to clean your home once per week;
hiring someone to maintain a garden or lawn;
hiring a chauffeur or cook;
being able to hire a personal assistant or nurse if you need assistance for health reasons;
being able to buy appropriate presents for friends and relatives on holidays, birthdays, etc.;
donating $1,000 to charity each year (as opposed to less than $100);
donating $10,000 to charity each year (as opposed to $1,000).

The order was fixed but reversed for half the subjects. Order had no effect on any measures of interest and is ignored. (And likewise for the order of question types described later.) After each item, the subject answered the following:

How does this affect what is important to you about your life as a retiree or senior?

* I don't care about this at all.
* This would be nice, but it would have little effect.
* This would have a noticeable effect.
* This would have a large effect.
* This is absolutely essential.

The last 20 items consisted of 10 items about direct utility measurement and 10 about risk. Five of the utility items were of this form:

> Which would have a greater effect on what is important to you about your life as a retiree or senior?
>
> * The difference between a household annual (pre-tax) income of $40,000 and [$50,000, $60,000, $70,000, $80,000, $90,000], or
> * The difference between [$50,000, $60,000, $70,000, $80,000, $90,000] and $120,000.

The figures in brackets were for the intermediate value, which increased from $50,000 to $90,000 over the five pages (or decreased, for half the subjects). Then the sequence was repeated, again with $40,000 as the lowest income, but with all other differences from $40,000 multiplied by 3, so that the steps were in increments of $30,000 instead of $10,000 and the top income was $280,000 instead of $120,000. (Order of the two sequences was reversed for half the subjects.)

The other 10 pages (which came first for half the subjects) were of the form:

> Supposed you had a choice of two investments for retirement. Each would provide your sole income during your entire retirement at the given rate (the same for all years). Which would you choose?
>
> * This one would pay [$50,000, $60,000, $70,000, $80,000, $90,000] per year (in current dollars) throughout your retirement.
> * This one has a 50% chance of paying $40,000 per year and a 50% chance of paying $120,000.

The numbers used, and the orders, were the same as for the difference question. Because of this matching, I could directly compare the subject's risk attitude to the prediction of expected-utility theory.

## 3. RESULTS AND DISCUSSION

I calculated three measures for each subject. One, which I call necessity fever, was the slope of the linear regression of the subject's ratings (0–4) of the 36 expenditure items on the mean ratings of all the subjects. A high positive slope indicated that the subject rated items as essential when they received such high ratings from others, and as unnecessary when others gave them low ratings. A low slope indicated a tendency toward smaller differences in ratings between "essential" and "inessential" items (as determined from other subjects' ratings), hence to have higher than average relative utility for the luxury items, which were, presumably, those that most subjects rated as less than essential. A low slope should predict a less concave (more linear) utility function for money.

The other two measures were simply the mean responses to the difference items and the gamble items, where one indicates that the subject accepted the gamble or thought that the difference between the intermediate and high amounts was larger than the difference between the low and intermediate amounts. These means would be 0.7 (between the third and fourth response option) for those who were risk neutral and had linear utility functions (assuming that these subjects would be indifferent when the intermediate value was equidistant from the high and low values, so that they would respond randomly). Numbers lower than 0.7 indicated risk aversion or concave utility.

The means were 0.22 for the gambles and 0.42 for the difference measures. Subjects were generally risk averse and had concave utility functions. The difference between gambles and difference measures was significant, which indicates that risk aversion cannot be explained entirely in terms of the utility function as measured by difference judgments. Indeed, the two means were uncorrelated across subjects ($r = 0.11$, $p = 0.34$).

Of greatest interest were the correlations of these two measures with the necessity-fever measure. As hypothesized, the correlation between slope, the necessity-fever measure, and the difference measure was negative and significant ($r = -0.41$, $p = 0.0002$). However, the correlation between necessity fever and the gamble measure was essentially zero ($r = 0.05$, slightly in the wrong direction). It is unlikely that this result is due to the unreliability of the gamble measure itself, as the 10 items had a reliability ($\alpha$) of 0.88. Moreover, the two dependent correlations (0.05 and −0.41) were significantly different ($p = 0.0008$).

The variance of the risk measure was lower than that of the difference measure (0.062 versus 0.118, $p = 0.0060$ for the difference, $p_{rep} = 0.96$). This result implies that people differ more in their utility functions than what we would assume from their risk preferences.

Several other studies attempted to replicate this result. One did so successfully with students. But another, also with students, failed to find a significant effect when the utility measures (gamble and difference) came before the luxury measures. Although I made no direct comparison of studies, it is possible that the luxury measures are helpful in thinking about the utility of money in retirement, thus benefiting the difference measure but not the gamble measure, which may still focus people on the risk itself.

## 4. CONCLUSION

Asking people about risk preferences using hypothetical gambles may lead to choices that fail to maximize their expected utility. In particular, some people may have substantial utility for luxuries, so that they ought to be willing to take risks in hopes of being able to afford those luxuries. Others have no use for luxuries and have no conflict with the single goal of trying to insure a no-frills retirement. These two extreme types do not seem to be differentiated by their risk attitude as assessed from hypothetical gambles. But, if we ask them about their utility for money using a method of comparing differences, the results do reflect their different tastes. The use of direct questions about utility could lead to financial advice. For example, a risk lover with no interest in luxuries might be told, "Why take risks? What are you going to do if you make a lot of money? Do you care that much?" Of course, risk itself has consequences for utility in terms of anxiety, regret, and disappointment over the long term, so these factors should be considered too.

More generally, the present results cast doubt on the use of hypothetical gambles to measure utility functions, and they suggest that the use of a simplified measure based comparison of differences is feasible. Researchers often talk about "von Neuman/Morgenstern utility" as if it were some special sort of thing that is related specifically to gambles. Yet, our interest in utility stems from the idea that it is a measure of goodness, that is, the extent to which our goals are achieved. If responses to gambles do not measure utility in this sense, we have better alternative measures. To define utility in terms of responses to gambles is like defining time in terms of the output of a sundial.

To be sure, it is possible that other measures using hypothetical decisions with probabilistic outcomes could do better than the gambles used here. For example, Kusev et al. (2009) and Jones and Oaksford (2011) found that utility functions differed depending on whether the choices were gambles, precautions, or transactions. It is also possible that the direct judgment method used here has other problems that would render it less useful in other contexts.

The present results might be taken as a sign that utility is unstable, and that, therefore, risk preferences are unstable. Yet another way to look at them is to say that the term "preference" is somewhat ambiguous between "what I choose now" and "what is best for me." Responses to gambles may reflect the former but not the latter.

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## REFERENCES

Baron, J. (1997). Biases in the quantitative measurement of values for public decisions. *Psychol. Bull.* 122, 72–88.

Baron, J. (2008). *Thinking and Deciding*, 4th Edn. New York: Cambridge University Press.

Jones, S., and Oaksford, M. (2011). Transactional problem content in cost discounting: parallel effects for probability and delay. *J. Exp. Psychol. Learn. Mem. Cogn.* 37, 739–747.

Krantz, D. H., Luce, R. D., Suppes, P., and Tversky, A. (1971). *Foundations of Measurement*, Vol. 1. New York: Academic Press.

Kusev, P., van Schaik, P., Ayton, P., Dent, J., and Chater, N. (2009). Exaggerated risk: prospect theory and probability weighting in risky choice. *J. Exp. Psychol. Learn. Mem. Cogn.* 35, 1487–1505.

Schoemaker, P. J. H. (1993). Determinants of risk taking: behavioral and economic views. *J. Risk Uncertain* 6, 49–73.

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# Information integration in risky choice: identification and stability

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How is information integrated across the attributes of an option when making risky choices? In most descriptive models of decision under risk, information about risk, and reward is combined multiplicatively (e.g., expected value; expected utility theory, Bernouli, 1738/1954; subjective expected utility theory, Savage, 1954; Edwards, 1955; prospect theory, Kahneman and Tversky, 1979; rank-dependent utility, Quiggin, 1993; decision field theory, Busemeyer and Townsend, 1993; transfer of attention exchange model, Birnbaum, 2008). That is, (some transform of) probability is multiplied by (some transform of) reward to give a value for a risky prospect, and the prospect with the maximum value is then chosen.

Here I argue that information integration in risky decision-making may be additive. Integration is additive in other domains and, if cognitive processes are shared, integration may be additive in risky choice too. Further, although valuations of risky prospects show multiplicative integration of risk and reward, integration is additive for judgments of attractiveness and, if risky decisions are based on attractiveness rather than valuation, integration in risky choice may be additive. Finally, I show that, for simple risky choices, an additive model can mimic a multiplicative model, and vice versa. Implications for the assessment of the stability of risky preference are profound – stable parameters in the multiplicative model will correspond with different stable parameters in the additive model and, further, the mode of integration itself may vary from time to time or context to context.

## JUDGMENTS OF NON-RISKY PROSPECTS

In a wide variety of decisions that do not involve risk, the additive model describes people's valuation of options better than the multiplicative model. For example, people average across descriptive adjectives when judging the likeability of a person (Anderson, 1981). In consumers' decision-making, information is averaged over attributes (Troutman and Shanteau, 1976). Prior expectancies are averaged with perceptual experiences in judging the quality of a wide variety of products (Dougherty and Shanteau, 1999). Preferences for sandwich and drink lunches involve an additive combination of information (Shanteau and Anderson, 1969). When pretending to be Father Christmas, children combine deservingness and achievement information additively to decide what present a child should receive (Anderson and Butzin, 1978). To the extent that common cognitive processes operate in all decisions, the additive model may also be operating in decisions involving risk.

## JUDGMENTS OF RISKY PROSPECTS

Buying prices, selling prices, bids, and certainty equivalents are often used to value risky options. For example, Tversky (1967a,b) had inmates give the minimum price for which they would sell an opportunity to play a simple gambles of the form "$p$ chance of $x$ otherwise nothing." Tversky found that there was a $p$ by $x$ interaction when predicting price but not logarithm of price and thus Tverksy rejected the additive model and concluded that his data were well described by a subjective expected utility model with a power law utility function and a subjective probability function. This finding has been replicated with more complicated gambles of the form "$p$ chance of gaining $x$ and $q$ chance of loosing $y$" (Anderson and Shanteau, 1970), when risks and rewards were presented as verbal phrases (e.g., "a somewhat likely chance to win a watch") rather than as numbers (Shanteau, 1974), and for strength-of-preference judgments for pairs of gambles (Mellers et al., 1992a). In contrast, ratings of favorableness, attractiveness, and the likelihood of playing are better described by an additive model (Sjöberg, 1968; Levin et al., 1985; Mellers et al., 1992b; Mellers and Chang, 1994). Multiplicative integration for valuations and additive integration for attractiveness has been found within the same experiment (e.g., Mellers et al., 1992a; Mullet, 1992).

It is not obvious to me whether choices will be more closely linked to valuation or attractiveness judgments. To the best of my knowledge, no one has explicitly compared additive models with multiplicative models using choice data. It may be that an additive model proves successful.

## THE IMPORTANCE OF A COMPLETE CHOICE MODEL

The information integration process cannot be considered in isolation from other cognitive steps. For example, because the logarithmic transform turns summing into multiplying $[\log(a)+\log(b)=\log(ab)]$ and an exponential transform turns multiplying into adding $[\exp(a)\exp(b) = \exp(a+b)]$, one must model the possible transformation of choice attributes into their subjective value, the integration of these values, and the translation of integrated values into a choice. In some circumstances multiplicative and averaging processes are equivalent. For example, Massaro and Friedman (1990) show that when information is combined additively in a perceptron (Rosenblatt, 1958) as a linear sum of input activations and a subsequent sigmoid transform is applied, this model is equivalent, for the case of two responses, to the (multiplicative) fuzzy logic model (Oden and Massaro, 1978).

## MATHEMATICAL SPECIFICATION OF THE MODEL

In the following modeling I show that a multiplicative and additive model can mimic one another. The valence $V(p_i, x_i)$ of a simple risky outcome $G_i$ of the form "$p_i$ chance of $x_i$ otherwise nothing" is given by

$$V(p_i,x_i)=w_1 s(p_i)+w_2 U(x_i)+w_3 s(p_i)U(x_i), \tag{1}$$

where $s(.)$ is the subjective probability function and $U(.)$ is the utility function and the subscript $i$ indexes different gambles. Without loss of generality, I constrain the $w$s to be in the range 0–1 and $w_1 + w_2 + w_3 = 1$. The restricted model with $w_1 + w_2 = 1/2$ and $w_3 = 0$ is the additive model. The restricted model with $w_1 = w_2 = 0$ and $w_3 = 1$ is the multiplicative model.

To provide a complete model of choice, I use Luce's choice rule to give the probability of choosing gamble $G_i$ from a set of $N$ gambles.

$$P(G_i)=\frac{V(p_i,x_i)^{\phi}}{\sum_{j=1}^{N} V(p_j,x_j)^{\phi}}, \tag{2}$$

$\phi$ is a free parameter which produces chance responding when $\phi = 0$ and increasingly deterministic as $\phi$ increases. Utility is assumed to be a power function of money:

$$U(x_i)=x_i^{\gamma}, \tag{3}$$

where $\gamma$ is a free parameter greater than zero. When $0 < \gamma < 1$, the utility function is concave. Subjective probability is assumed to follow the form suggested by Wu and Gonzalez (1996):

$$s(p_i)=\frac{p_i^{\beta}}{\left(p_i^{\beta}+(1-p_i)^{\beta}\right)^{1/\beta}}, \tag{4}$$

where $\beta$ is a free parameter greater than zero. When $0 < \beta < 1$, the subjective probability function has an inverse-S-shape.

## MODEL MIMICRY

To illustrate how additive and multiplicative models can mimic one another, I generated data from a base model with $\gamma = 1/2$, $\beta = 2/3$, $\phi = 1$, and $w_1 = w_2 = w_3 = 1/3$. The exact parameter values are not crucial to the argument. These values are loosely based on the well established findings of a concave utility function, an inverse-S-shaped probability weighting function, and probability matching. These particular $w$ parameters give the subjective value of a gamble as the sum of the subjective probability, subjective utility, and their product.

The choice set used is the set of all possible choices of the form "$p_1$ chance of $x_1$ otherwise nothing" or "$p_2$ chance of $x_2$ otherwise nothing" that can be constructed using probabilities .1, 0.3, 0.5, 0.7, and 0.9 and amounts 20, 40, 60, 80, and 100. (In modeling, amounts were scaled for convenience by dividing by 100 so that amounts lay on the same interval, roughly, as probabilities.) Raw data take the form of the probability of choosing Gamble 1 according to the base model.

**Figure 1** shows how the fit of the model to these data varies with the parameter choice. Fit is calculated as the likelihood that the model could generate the data. Obviously the base model which generated the data fits best. But other models fit well too. The panels in **Figure 1** shows the likelihood surfaces as model parameters deviate away from the best fit. High points on the surface represent good model fits. **Figure 1A** show how such simple choices do not constrain the forms of the utility and weighting functions very well. The broad flat maximum on the likelihood surface shows that, although $\gamma = 1/2$ and $\beta = 2/3$ provides the best fit, these parameters can vary considerably with only a minimal effect on the model fit (see Zeisberger et al., in press). This is not of central concern here, but is quite often overlooked in modeling decision-making under risk. **Figure 1B** show how the model fit is affected by switching the mode of information integration. As $w_3 = 1 - w_1 - w_2$ (without loss of generality), the points in the horizontal plane represent all possible mixtures of information integration. At the leftmost corner of the plot where $w_1 = w_2 = 0$ and $w_3 = 1$ (i.e., a purely multiplicative model) the fit is somewhat compromised. The other two corners of the surface represent a model where only probability is weighted or where only amount is weighted, and are also similarly badly fitting. But for a ridge in the middle of the surface (the area colored red), quite large variation in the information integration has a small effect. **Figure 1C** shows the most important result. Here, the error surface is plotted as a function of $\phi$, the determinism parameter in the Luce choice rule, and $w_3$ [I constrained $w_1 = w_2 = (1 - w_3)/2$ here]. There is a ridge of roughly equal likelihood which passes through the base model at $\phi = 1$, $w_3 = 1/3$ where the log likelihood of the data given the model is −200.972. At one end, where $w_3 = 0$ and the model is completely additive, the log likelihood is −201.060. At the other end, where $w_3 = 1$ and the model is completely multiplicative, the log likelihood is −201.308. This means that, whatever mode of integration one chooses for the model, it can be completely compensated for by varying the degree of determinism in the choice rule. The more additive the model, the higher the value of $\phi$ needed to compensate. This result holds for a purely additive base model and a purely multiplicative base model. In short, with choices between these simple gambles, one cannot discriminate between additive and multiplicative models of decision under risk.

## DISCUSSION

This special issue is about the stability, or otherwise, of risky preferences across time or context. To assess the stability of preferences, one can identify and fit a model of risky choice to data from two or more times or contexts and then compare parameters across times or contexts (see Zeisberger et al., 2011, for a review). Here, I have suggested that information integration in risky choice may be additive rather than multiplicative. I have shown that, for two-branch choices with one non-zero branch, additive and multiplicative models can mimic one another. There are two implications of these findings for the stability of risky preferences. First, even if some parameter value are stable over time, this does not mean that correct model has been identified. Because an additive model can mimic a multiplicative model, stable parameters from the multiplicative model map on to stable—but different—parameters in the additive model: the data do not discriminate between models, and the parameter values from a particular model cannot be directly interpreted outside of the model. Second, even if there is stability in the utility and weighting functions (but see Stewart, 2009, for demonstrations of malleability), there may be variation in information integration over time or context. For example, Ordóñez and Benson (1997) find people switch integration rules under time pressure, and Mellers et al. (1992b) find that the mode of integration depends on the range of probabilities used in the question set.

In closing, I note that the ability of additive and multiplicative models to mimic one another offers an explanation for the success of the decision by sampling model I have proposed elsewhere (Stewart et al., 2006) in accounting for risky choice. In the model,

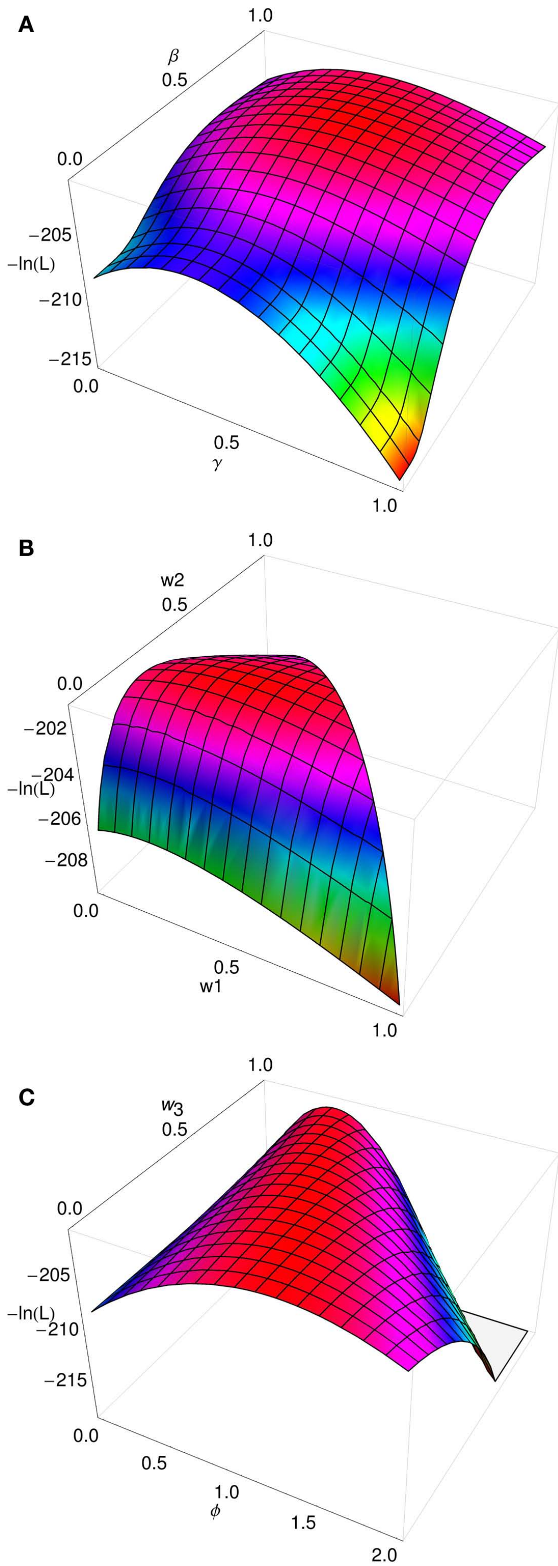


**FIGURE 1 | The (log) likelihood of the data given the model, ln (*L*). (A)** A wide range of utility and weighting function parameters provide good fits. **(B)** A wide range of integration modes provide a good fit. **(C)** Any integration mode can be fitted by adjusting response determinism. Non-graphed parameters match those of the base model.

attributes are selected and compared to other attributes in memory. Favorable comparisons are counted in an accumulator, and the prospect whose accumulator gets to threshold first is selected. Because, for each prospect, favorable comparisons are counted in a single accumulator, information about how well an amount compares to other amounts memory is effectively combined additively with information about how well a probability compares to other probabilities in memory. For example, the subjective value of a simple gamble like a "30% chance of winning \$100" is effectively the proportion of probabilities in memory less than 30% (because the target 30% will compare favorably to these) *plus* the proportion of amounts in memory less than \$100 (because the target \$100 will compare favorably to these). Despite the decision by sampling model combining risk and reward information additively, it is able to fit, for example, the classic paradoxes in Kahneman and Tverksy (1979) prospect theory paper (see Stewart and Simpson, 2008; Stewart, 2009) because it can vary in the degree of determinism in responding by altering the threshold to which accumulators race. In short, psychologically plausible process models of risky decision-making need not have an explicit multiplicative integration of information to provide a good descriptive account.

## REFERENCES

Anderson, N. H. (1981). *Foundations of Information Integration Theory*. New York: Academic Press.

Anderson, N. H., and Butzin, C. A. (1978). Integration-theory applied to children's judgments of equity. *Dev. Psychol.* 14, 593–606.

Anderson, N. H., and Shanteau, J. C. (1970). Information integration in risky decision making. *J. Exp. Psychol.* 84, 441–451.

Bernouli, D. (1738/1954). Expositions of a new theory of the measurement of risk. *Econometrica* 22, 23–36.

Birnbaum, M. H. (2008). New paradoxes of risky decision making. *Psychol. Rev.* 115, 453–501.

Busemeyer, J. R., and Townsend, J. T. (1993). Decision field theory: a dynamic-cognitive approach to decision making in an uncertain environment. *Psychol. Rev.* 100 432–459.

Dougherty, M. P. R., and Shanteau, J. (1999). Averaging expectancies and perceptual experiences in the assessment of quality. *Acta Psychol. (Amst)* 101, 49–67.

Edwards, W. (1955). The predictions of decisions among bets. *J. Exp. Psychol.* 50, 201–214.

Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–291.

Levin, I. R., Johnson, R. D., Russo, C. P., and Delden, P. J. (1985). Framing effects in judgment tasks with

varying amounts of information. *Organ. Behav. Hum. Decis. Process.* 36, 362–377.
Massaro, D. W., and Friedman, D. (1990). Models of integration given multiple sources of information. *Psychol. Rev.* 97, 225–252.
Mellers, B. A., and Chang, S. (1994). Representations of risk judgments. *Organ. Behav. Hum. Decis. Process.* 57, 167–184.
Mellers, B. A., Chang, S. J., Birnbaum, M. H., and Ordóñez, L. D. (1992a). Preferences, prices, and ratings is risky decision-making. *J. Exp. Psychol. Hum. Percept. Perform.* 18, 347–361.
Mellers, B. A., Ordóñez, L. D., and Birnbaum, M. H. (1992b). A change-of-process theory for contextual effects and preference reversals in risky decision making. *Organ. Behav. Hum. Decis. Process.* 52, 331–369.
Mullet, E. (1992). The probability (utility rule in attractiveness judgments of positive gambles. *Organ. Behav. Hum. Decis. Process.* 52 246–255.
Oden, G. C., and Massaro, D. W. (1978). Integration of featural information in speech perception. *Psychol. Rev.* 85, 172–191.
Ordóñez, L. D., and Benson, L. (1997). Decisions under time pressure: how time constraint affects risky decision making. *Organ. Behav. Hum. Decis. Process.* 71, 121–140.
Quiggin, J. (1993). *Generalized Expected Utility Theory: The Rank-Dependent Model*. Norwell, MA: Kluwer Academic Publishers.
Rosenblatt, F. (1958). The perceptron: a probabilistic model for information storage and organization in the brain. *Psychol. Rev.* 65, 386–408.
Savage, L. J. (1954). *The Foundations of Statistics*. New York: Wiley.
Shanteau, J. (1974). Component processes in risky decision making. *J. Exp. Psychol.* 103, 680–691.
Shanteau, J. C., and Anderson, N. H. (1969). Test of a conflict model for preference judgment. *J. Math. Psychol.* 6, 312–325.
Sjöberg, L. (1968). Studies of the rated favorableness of offers to gamble. *Scand. J. Psychol.* 9, 257–273.
Stewart, N. (2009). Decision by sampling: the role of the decision environment in risky choice. *Q. J. Exp. Psychol.* 62, 1041–1062.
Stewart, N., Chater, N., and Brown, G. D. A. (2006). Decision by sampling. *Cogn. Psychol.* 53, 1–26.
Stewart, N., and Simpson, K. (2008). "A decision-by-sampling account of decision under risk," in *The Probabilistic Mind: Prospects for Bayesian Cognitive Science*, eds L. N. Chater and M. Oaksford (Oxford, England: Oxford University Press), 261–276.
Troutman, C. M., and Shanteau, J. (1976). Do consumers evaluate products by adding or averaging attribute information? *J. Consum. Res.* 3, 101–106.
Tversky, A. (1967a). Utility theory and additivity analysis of risky choices. *J. Exp. Psychol.* 75, 27–36.
Tversky, A. (1967b). Additivity, utility, and subjective probability. *J. Math. Psychol.* 4, 175–201.
Wu, G., and Gonzalez, R. (1996). Curvature of the probability weighting function. *Manage. Sci.* 42, 1676–1690.
Zeisberger, S., Vrecko, D., and Langer, T. (2011). Measuring the time stability of prospect theory preferences. *Theory Dec.* doi: 10.1007/s11238-010-9234-3. [Epub ahead of print].

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# Decision by sampling and memory distinctiveness: range effects from rank-based models of judgment and choice

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To what extent are preferences for risk – and for other economic quantities – stable, and to what extent are they malleable and context-dependent? Judgments and choices are strongly influenced by the context of available options in both the laboratory and the real world (e.g., Parducci, 1995; Sharpe et al., 2008), and this applies both to choices between risky options and more generally (Stewart et al., 2003). What cognitive processes underpin these contextual influences? According to the decision by sampling model (DbS: Stewart et al., 2006), judgments of a stimulus in a context depend solely on the *relative ranked position* of the stimulus within the remembered or experienced context of judgment. The claim that only relative ranked position matters appears, however, to contradict both empirical data and an earlier model of judgment, range frequency theory (RFT: Parducci, 1965, 1995), according to which the position of a stimulus with respect to the highest and lowest stimuli in the context (its range position) also matters. Here we show that a purely rank-based approach can account for apparent range effects when the relative memorability of contextual items, as independently determined by a memory model (Brown et al., 2007), is taken into account.

Such a demonstration is important for several reasons. In particular, it is important to understand whether the skew of a distribution (e.g., the degree of inequality of an income distribution) influences the judgments of items (e.g., individuals' own incomes) within that distribution. If judgments are based solely on relative rank (as DbS claims), there should be no effects of distribution skewness – yet such effects are frequently observed. For example, there is a tension between the claim that income inequality within a society influences various indices of societal well-being (e.g., Wilkinson and Pickett, 2009) and the claim that individuals are primarily or solely concerned with the ranked position of their income (Boyce et al., 2010). Here we address this tension directly.

The Decision by Sampling model assumes that, when making a judgment, people draw a sample from memory, the choice environment, or both. They then compare, ordinally, the to-be-judged stimulus with each sample item. Consider the problem of determining one's wage satisfaction. According to DbS, one might call to mind two individuals who get paid less ($N_{\text{lower}} = 2$), and three individuals who get paid more ($N_{\text{higher}} = 3$). That is, one is the $i$'th most highly paid person out of $n$, where $i = 3$ and $n = 6$. The resulting estimate of one's relative ranked position, $F_i$, is according to DbS simply:

$$F_i = \frac{i-1}{n-1} = \frac{N_{\text{lower}}}{N_{\text{lower}} + N_{\text{higher}}} = 0.4 \qquad (1)$$

Crucially, such a judgment can be based on cognitively basic ordinal binary comparisons.

The rank-based process in DbS explains how changes in the distribution of contextual items will influence judgment. Consider for example a positively skewed set of wages, with many relatively low earners and few relatively high earners. Such a distribution is illustrated in **Figure 1A**, along with a range-matched negatively skewed distribution. If satisfaction comes from a wage's relative ranked position in its context, the function relating satisfaction to wage will be concave for a positively skewed distribution, because relative ranked position will rise faster with income at the lower part of the distribution. As one moves higher up the positively skewed distribution, it becomes progressively more expensive to buy each additional increment in relative rank. And indeed, participants' judgments are described by just such a concave function, with a corresponding convex function being associated with a negatively skewed distribution (**Figure 1C**). The judgments are taken from Brown et al. (2008) and are here normalized to lie between 0 and 1. **Figure 1B** shows a second pair of distributions designed to examine relative rank effects – the highlighted item pairs have the same absolute value, are located in distributions matched for mean and endpoints, and hence differ only in their relative rank within their respective contexts. Again, the satisfaction associated with each hypothetical wage is influenced by its relative rank (**Figure 1D**). More generally, DbS has been used to explain why apparent utility curves have the shape they do (e.g., the concave relationship between utility and money arises because of the positively skewed distribution of financial gains in the environment) and more specifically to give a process-level account of why models such as Prospect Theory (Kahneman and Tversky, 1979), work well descriptively (Stewart et al., 2006; Stewart, 2009).

Although numerous studies appear consistent with the relative rank principle in DbS, additional effects of the range position of stimuli are often observed. DbS was motivated partly by, and inherits much of the support for, an earlier – and highly influential – account of contextual judgment: RFT. Although less oriented toward providing a process-level account, and focused more on experimental rather than remembered contexts, RFT shares with DbS the assumption that the relative ranked position of an item within its context will affect its judgment. However, unlike DbS, RFT predicts that the position of an item with respect to the highest and lowest stimuli will also affect its judgment. Here we aim to reconcile the apparent presence of range effects (as postulated by RFT) with the purely rank-based processes of DbS. In RFT, $M_i$, the subjective psychological magnitude of $x_i$, (where $x_i$ is the $i$th largest in a set of $n$ stimuli) will be given by:

$$M_i = wR_i + (1-w)F_i \qquad (2)$$

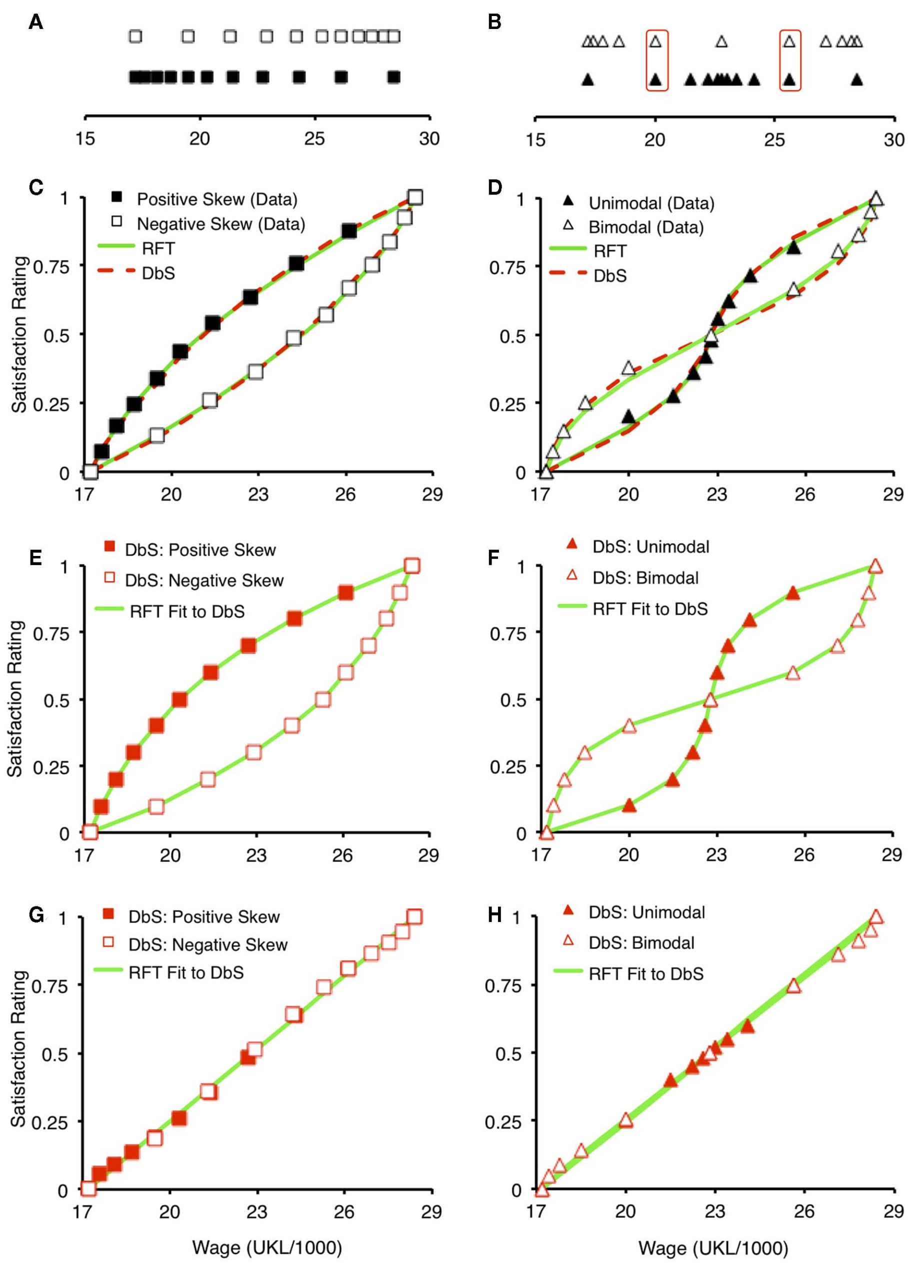


**FIGURE 1 | Comparison of the predictions of RFT and the combined DbS-SIMPLE model (see text for details). (A)** Positively and negatively skewed wage distributions. **(B)** Bimodal and unimodal wage distributions. **(C,D)** Fit of RFT and DbS-SIMPLE to wage satisfaction judgments. **(E,F)** Predictions of DbS-SIMPLE model with high memory discriminability, and fit of RFT to those predictions. **(G,H)** Predictions of DbS-SIMPLE model with low memory discriminability, and fit of RFT to those predictions.

where $R_i$ is the range value of $x_i$:

$$R_i = \frac{x_i - x_1}{x_n - x_1} \quad (3)$$

and $F_i$ is the relative ranked ordinal position (or "frequency value") of the item in the ordered set, as used in DbS and given by Eq. 1 above (although DbS assumes a retrieved rather than experimentally provided context).

Thus (according to RFT), the subjective magnitude of a stimulus in a context will depend on (a) the position of the stimulus along a line joining the lowest and highest points in the set and (b) the rank ordered position of the stimulus. In Eq. 2, $w$ is a weighting parameter which is often estimated at approximately 0.5 for physical judgments.

Range frequency theory has been highly successful as a descriptive account of judgments in context (Parducci, 1995). However, an important part of RFT's success comes from its inclusion of a range-based as well as a rank-based component. For example, the solid green lines in **Figures 1C,D** show the fit of RFT to the wage satisfaction judgments. The estimated values of $w$ that led to this fit were 0.32 (C) and 0.43 (D), suggesting that both range and rank affect judgment (see Eq. 2).

It might therefore appear to be a serious limitation of DbS that it predicts only effects of relative rank and not additional effects of range (and hence, as noted earlier, of skew). Here, however, we argue that apparent range effects could reflect the reduced psychophysical discriminability of items in relatively crowded regions of psychological space, as predicted by models of memory. For example, the SIMPLE model of memory (Brown et al., 2007) views memory retrieval as a discrimination task. An important dimension along which discrimination occurs is assumed to be temporal (Brown et al., 2009), as is needed to explain forgetting, but here we focus on the dimension along which judgment must be made (e.g., the amount of a wage). Central to the model is the notion of distinctiveness (intuitively: items are viewed as distinctive, and hence discriminable in and retrievable from memory, to the extent that they occupy relatively isolated locations in multidimensional psychological space).

We first provide an intuitive example. Consider the median wage (20) highlighted in the following context of wages: [5 10 15 **20** 23 24 25]. If all contextual items are included in the sample, the relative ranked position of 20 will be 0.5 [$N_{\text{lower}}/(N_{\text{higher}} + N_{\text{lower}}) = 3/6$]. Suppose however that the three wages above the median are less distinctive in memory (because they are close to one another), and that each has a probability of being included in the sample of just 0.5. The judgment of the median wage will then be $(N_{\text{lower}})/(N_{\text{higher}} + N_{\text{lower}}) = 3/4.5 = 0.67$. This falls between the relative ranked position of 20 (which was 0.5) and the range position of 20 (which, by Eq. 3, is 0.75). Thus, a purely rank-based account such as DbS may be able to account for apparent range effects when the distinctiveness and hence availability in memory of contextual items is incorporated. We illustrate with a basic implemented model.

According to the SIMPLE model, the confusability of any two items in memory will be a reducing exponential function of the distance between them in psychological space:

$$\eta_{i,j} = e^{-cd_{i,j}} \tag{5}$$

where $\eta_{i,j}$ is the similarity between items $i$ and $j$ and $d_{i,j}$ the distance between them (here, the distance along the dimension of judgment that separates the two items – e.g., a difference in wages). We assume that the probability of an item being included in a sample used for judgment will depend on its retrievability. In SIMPLE, the retrievability of an item will depend on its discriminability, where the discriminability of item $i$ is inversely proportional to its summed similarity to every other potentially available stimulus. Specifically, the discriminability of the trace for item $i$, $D_i$, is given by:

$$D_i = \frac{1}{\sum_{k=1}^{n} \left(\eta_{i,k}\right)} \tag{6}$$

where $n$ is the number of available response alternatives (this will be just the number of available potential comparison stimuli). Discriminability is converted into predicted recall probability by taking into account the possibility of omissions. If $D_i$ is the discriminability given by the preceding equation, the recall probability $P_i$ is given by:

$$P_i = \frac{1}{1 + e^{-s(D_i - t)}}, \tag{7}$$

where $t$ is the threshold (such that if discriminability is below a threshold an item cannot be retrieved) and $s$ determines the slope of the transforming function (effectively, how noisy the omission threshold is).

We now illustrate, using the wage satisfaction data, how a DbS model can give rise to apparent range effects when supplemented by this model of memory distinctiveness and retrieval. The model assumes that the probability of each item being included in the sample that determines judgment is predictable from the SIMPLE model (Eqs 5–7 above). The satisfaction with each wage was assumed to be based purely on the relative rank of each wage within its context (as in Eq. 1), but with each item weighted by the probability of it being included in the sample.

The fit of the model to the wage satisfaction data (**Figures 1C,D**) is shown as a dashed red line. Parameter values were $c = 2.11$, $t = 0.47$, $s = 4.24$ for all four (positive, negative, unimodal and bimodal) distributions. Despite not including any range-based component, the model fits the data as well as does RFT (solid green line) – fits were not statistically distinguishable on the illustrative data, although we note that the combined model has additional parameters. The reason for the combined model's behavior is as stated above – the items in relatively crowded regions of stimulus space are less distinctive and hence contribute less to the rank-based comparison process in DbS than they would if they were equally likely to enter (or carried equal weight within) the sample.

To explore the combined (SIMPLE + DbS) model, we derived its predictions under various assumptions about memory discriminability, then examined how well RFT would fit the model's behavior. We first set $c$ to a large number, with the result that all items could be perfectly discriminated and all contributed to the rank-based judgment. Results are shown in **Figures 1E,F**, where it is evident that strong rank effects are produced – as expected, because items are equally discriminable and all contribute to judgment. The solid lines show the SSE-minimizing fit of RFT to the data generated from the model; the estimated value of $w$ was 0 (i.e., RFT accommodated the fact that only rank-based comparison occurred).

**Figures 1G,H** show the predictions of the model when $c = 1.8$ (left column) and 1.6 (right column). Parameters $t$ and $s$ were set at 0.8 and 5 respectively for both pairs of distributions. The best-fitting version of RFT estimated $w = 0.95$, indicating that the output of the rank-based model was interpreted by RFT as a predominantly range-based model.

In summary, apparent range effects can emerge from a purely rank-based judgment model when item discriminability is accommodated. Thus apparent range effects need not support RFT over purely rank-based accounts. Moreover, effects of distribution skew (e.g., income inequality) need not be inconsistent with the operation of purely rank-based judgments. Finally, we note that although the SIMPLE + DbS model behaves similarly to RFT under the conditions described above, the models are not formally identical and can make different predictions.

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## REFERENCES

Boyce, C. J., Brown, G. D. A., and Moore, S. C. (2010). Money and happiness: rank of income, not income, affects life satisfaction. *Psychol. Sci.* 21, 471–475.

Brown, G. D. A., Gardner, J., Oswald, A. J., and Qian, J. (2008). Does wage rank affect employees' well-being? *Ind. Relat.* 47, 355–389.

Brown, G. D. A., Neath, I., and Chater, N. (2007). A temporal ratio model of memory. *Psychol. Rev.* 114, 539–576.

Brown, G. D. A., Vousden, J. I., and McCormack, T. (2009). Memory retrieval as temporal discrimination. *J. Mem. Lang.* 60, 194–208.

Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–291.

Parducci, A. (1965). Category judgment: a range-frequency model. *Psychol. Rev.* 72, 407–418.

Parducci, A. (1995). *Happiness, Pleasure and Judgment: The Contextual Theory and its Applications*. Mahwah, NJ: Lawrence Erlbaum Associates.

Sharpe, K. M., Staelin, R., and Huber, J. (2008). Using extremeness aversion to fight obesity: policy implications of context dependent demand. *J. Consum. Res.* 35, 406–422.

Stewart, N. (2009). Decision by sampling: the role of the decision environment in risky choice. *Q. J. Exp. Psychol.* 62, 1041–1062.

Stewart, N., Chater, N., and Brown, G. D. A. (2006). Decision by sampling. *Cogn. Psychol.* 53, 1–26.

Stewart, N., Chater, N., Stott, H. P., and Reimers, S. (2003). Prospect relativity: how choice options influence decision under risk. *J. Exp. Psychol. Gen.* 132, 23–46.

Wilkinson, R., and Pickett, K. (2009). *The Spirit Level: Why More Equal Societies Almost Always do Better*. London: Allen Lane.

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# Testing theories of risky decision making via critical tests

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Whereas some people regard models of risky decision making as if they were statistical summaries of data collected for some other purpose, I think of models as theories that can be tested by experiments. I argue that comparing theories by means of global indices of fit is not a fruitful way to evaluate theories of risky decision making. I argue instead for experimental science. That is, test critical properties, which are theorems of one model that are violated by a rival model. Recent studies illustrate how conclusions based on fit can be overturned by critical tests.

Elsewhere, I have warned against drawing theoretical conclusions from indices of fit (Birnbaum, 1973, 1974, 2008a): Fit changes under monotonic transformation of the dependent variable and scaling of stimuli. An index of fit depends on experimental design; it depends on parameters and how they are estimated. Different indices can lead to opposite conclusions. A wrong model can achieve a "good" fit, and it can even fit better than the model used to generate the data. I will not add here to this list of problems; instead, I argue in support of traditional science.

A theory is a set of statements satisfying five philosophical criteria: (1) it is *deductive* in that the phenomena to be explained can be derived from the theory; (2) it is *meaningful*; that is, it can be tested (potentially falsified); (3) *predictive*: if we knew the theory, in principle, we could have predicted the events to be explained; (4) *causal*: it specifies in principle how to alter the phenomena via manipulation; and (5) *general*: premises used in a theory are *laws*; they are not assumed or denied from case to case.

In deduction, when premises are true, conclusions must also be true. However, if a conclusion is assumed (or empirically established), it says nothing about the truth of the premises. Therefore, we cannot "prove" a theory via experiments. However, if implications deduced from a theory are false, we know the theory is false. So we can test a theory by testing its theorems. A test is an opportunity to disprove, but failure to disprove does not prove a theory.

The term "model" refers to a special case of a theory that also includes all of the operational definitions and simplifying assumptions needed to apply a theory to a particular paradigm.

The classic paradoxes of Allais (1953) are examples of critical tests. These paradoxes lead expected utility (EU) theory into self-contradiction. They do not require us to estimate any parameters from data, nor do we need to compute an index of fit, because the "paradoxical" behavior, if real, shows that no parameters will work. Models proposed to account for these paradoxes include prospect theory (PT; Kahneman and Tversky, 1979), cumulative prospect theory (CPT) (Tversky and Kahneman, 1992), and the transfer of attention exchange (TAX) model (Birnbaum, 1999).

Because people often make different responses when the same choice problem is repeated, it is useful to distinguish instability of preference due to random error from that due to a false theory. The true and error model assumes that different people may have different "true" preferences when presented with a given choice problem, that different choice problems may have different error rates, and that some individuals may have more "noise" in their data than others (Birnbaum, 2008c, Appendix D; Birnbaum and Gutierrez, 2007). This model provides a neutral standard for testing critical properties, such as Allais paradoxes and new paradoxes that distinguish between CPT and TAX.

The original version of PT had a number of problems that required a list of "editing rules," added to excuse the model from potential evidence against it. For example, PT implied that people would violate stochastic dominance in cases where all possible consequences of one gamble are better than the best consequence of the other. So a rule was added to say that people satisfy dominance whenever they detect it, but it did not say when people detect it. CPT solved this problem, because it implies that people always satisfy stochastic dominance, apart from random error.

A configural weighting model (Birnbaum and Stegner, 1979), implies that dominance is not always satisfied. A simple version of this model was fit to risky decisions, where it was renamed the TAX model, and a recipe was constructed for choices in which the model predicts a violation (Birnbaum, 1997). Here is an example:

| | |
|---|---|
| Urn *A* contains: | 85 Tickets to win \$96 |
| | 5 Tickets to win \$90 |
| | 10 Tickets to win \$12 |
| Urn *B* contains: | 90 Tickets to win \$96 |
| | 5 Tickets to win \$14 |
| | 5 Tickets to win \$12 |

One ticket will be drawn randomly from the chosen urn, to determine the prize. Which urn would you choose? According to CPT, people should prefer *B*. One need not estimate any parameters, because CPT makes this prediction for any set of parameters and any monotonic value and probability weighting functions. Although TAX can satisfy stochastic dominance (EU is a special case of TAX), it violates dominance in this choice for plausible parameters (Birnbaum and Navarrete, 1998; Birnbaum, 2004a, 2005, 2008b).

A critical property is a theorem of one theory that is violated by a rival. In this case, CPT with any parameters implies people must choose *B* (apart from random error), but TAX with parameters predicts *A*. Such choices have now been tested with thousands of people, using a dozen formats for presenting choices. About 60–70% of undergraduates violate CPT by choosing *A* instead of *B*, contrary to stochastic dominance, in a single choice of this type. When corrected for unreliability of responses, the estimated rate of "true" violation is even higher (Birnbaum, 2004b, 2008b, Table 11).

According to the TAX model, the utility of the gamble is a weighted average of the utilities of the consequences, with weights that depend on probability and on the ranks of the consequences. Because the weighting function for probability is negatively accelerated, a branch with five tickets (0.05) ends up getting relatively more weight compared to its objective probability, which causes *A* to appear better because the 0.05 branch to win $90 in *A* (and the 0.05 branch to win only $14 in *B*) get more weight.

Other critical tests also refute CPT. Empirical studies of 12 theorems of CPT show that neither version of PT can be retained as descriptive of risky decision making (Birnbaum, 2008b,c).

Brandstätter et al. (2006) proposed the priority heuristic (PH) based on an index of fit assessing how this model performed in describing the data used to generate the model. The PH is a variant of a lexicographic semiorder (LS) used by Tversky (1969) to describe violations of transitivity. They claimed PH was more often correct in predicting modal choices than either CPT or TAX, both of which are transitive models. But these conclusions reverse when parameters are estimated instead of fixed in advance; they reverse when we consider different sets of data, and most important: they reverse when we examine critical properties designed to test these theories.

The family of LS, including PH, must satisfy interactive independence. People should make the same decisions in these two choices:

| | |
|---|---|
| Choice 1: | |
| Urn *C* contains | 90 tickets to win $100 |
| | 10 tickets to win $5 |
| Urn *D* contains | 90 tickets to win $50 |
| | 10 tickets to win $20 |
| Choice 2: | |
| Urn *E* contains: | 10 tickets to win $100 |
| | 90 tickets to win $5 |
| Urn *F* contains: | 10 tickets to win $50 |
| | 90 tickets to win $20 |

According to PH, people should choose *D* (over *C*) and *F* (over *E*) because the lowest consequence is better and the difference ($15) exceeds threshold. According to any member of the LS family (with different orders of examining the attributes, different psychophysical functions on the attributes, and different thresholds) a person should either choose *C* and *E* or *D* and *F*, or be indifferent in both, but she should not switch, except by error, because any attribute that is the same in both alternatives (here probability is the same) should have no effect. Instead, the true and error model indicated that 63% of those tested switched their true preferences from *C* to *F* (after correcting for preference instability due to random error), demonstrating an interaction between probability and the prizes (Birnbaum, 2008c).

Other critical tests also refute LS and PH (Birnbaum, 2008c, 2010). PH may have looked "good" by means of an index of fit applied to certain studies using fixed parameters, but it has not been successful in predicting new results.

If a critical test is satisfied, it does not mean that the theory that implies it is "validated," "confirmed," or "proved." It merely means that the theory that implies it can be retained. However, the greater the number of interesting predictions that a theory makes that are satisfied, the more we are likely to bet on its predictions in the future. Thus, confidence in a theory can grow by induction, but scientific theories are always open to revision or refutation based on new evidence.

Does testing theories via critical properties mean that there is no role for model-fitting and parameter estimation? No. These serve two important functions: First, we should try to learn from our data where a model fits poorly, in order to devise new tests that have the potential to refute the model. Second, parameters are used to devise new tests between rival models.

For example, PH was devised to account for previously published data, such as those of Tversky (1969) who reported violations of transitivity consistent with a LS (Brandstätter, et al., 2006, 2008). Transitivity is the assumption that if *A* is preferred to *B* and *B* is preferred to *C*, then *A* should be preferred to *C*. Because PH can account for violations of transitivity and models like EU, CPT, and TAX cannot, transitivity is a critical property that has the potential to refute both CPT and TAX.

Just as the TAX model had been used to construct a test of stochastic dominance where violations of CPT should be observed, PH has been used to design new tests of transitivity to search for predicted violations of TAX and CPT that satisfy this critical property.

Birnbaum and Gutierrez (2007) and Regenwetter et al. (2010, 2011) carried out such tests, using designs similar to those of Tversky (1969), but they were not able to find much, if any, evidence for the predicted intransitive behavior. Birnbaum and Bahra (2007) devised three interlaced designs in which PH predicted violations of transitivity. Although they found evidence that perhaps as many as 4% of participants were partly or momentarily intransitive, they were not able to refute transitivity for the vast majority of cases. The PH was correct in predicting modal choices in only 18 of 60 new choices devised to test its predictions (30%).

This case illustrates how conclusions based on an index of fit can be ephemeral. What looks good by an index applied to selected data can look horrible when that model and its parameters are used to predict the results of a new study testing critical properties.

## REFERENCES


Allais, M. (1953). Le comportement de l'homme rationnel devant le risque: critique des postulats et axiomes de l'école Américaine. *Econometrica* 21, 503–546.

Birnbaum, M. H. (1973). The devil rides again: correlation as an index of fit. *Psychol. Bull.* 79, 239–242.

Birnbaum, M. H. (1974). Reply to the devil's advocates: don't confound model testing and measurement. *Psychol. Bull.* 81, 854–859.

Birnbaum, M. H. (1997). "Violations of monotonicity in judgment and decision making," in *Choice, Decision, and Measurement: Essays in Honor of R. Duncan Luce*, ed. A. A. J. Marley (Mahwah, NJ: Erlbaum), 73–100.

Birnbaum, M. H. (1999). "Paradoxes of Allais, stochastic dominance, and decision weights," in *Decision Science and Technology: Reflections on the Contributions of Ward Edwards*, eds J. Shanteau, B. A. Mellers, and D. A. Schum (Norwell, MA: Kluwer Academic Publishers), 27–52.

Birnbaum, M. H. (2004a). Causes of Allais common consequence paradoxes: an experimental dissection. *J. Math. Psychol.* 48, 87–106.

Birnbaum, M. H. (2004b). Tests of rank-dependent utility and cumulative prospect theory in gambles represented by natural frequencies: effects of format, event framing, and branch splitting. *Organ. Behav. Hum. Decis. Process* 95, 40–65.

Birnbaum, M. H. (2005). A comparison of five models that predict violations of first-order stochastic dominance in risky decision making. *J. Risk Uncertain* 31, 263–287.

Birnbaum, M. H. (2008a). Evaluation of the priority heuristic as a descriptive model of risky decision making: comment on Brandstätter, Gigerenzer, and Hertwig (2006). *Psychol. Rev.* 115, 253–262.

Birnbaum, M. H. (2008b). New paradoxes of risky decision making. *Psychol. Rev.* 115, 463–501.

Birnbaum, M. H. (2008c). New tests of cumulative prospect theory and the priority heuristic: probability-outcome tradeoff with branch splitting. *Judgm. Decis. Mak.* 3, 304–316.
Birnbaum, M. H. (2010). Testing lexicographic semiorders as models of decision making: priority dominance, integration, interaction, and transitivity. *J. Math. Psychol.* 54, 363–386.
Birnbaum, M. H., and Bahra, J. P. (2007). Transitivity of preference in individuals. *Society for Mathematical Psychology Meetings*, Costa Mesa, CA.
Birnbaum, M. H., and Gutierrez, R. J. (2007). Testing for intransitivity of preferences predicted by a lexicographic semiorder. *Organ. Behav. Hum. Decis. Process* 104, 97–112.
Birnbaum, M. H., and Navarrete, J. B. (1998). Testing descriptive utility theories: violations of stochastic dominance and cumulative independence. *J. Risk Uncertainty* 17, 49–78.
Birnbaum, M. H., and Stegner, S. E. (1979). Source credibility in social judgment: bias, expertise, and the judge's point of view. *J. Pers. Soc. Psychol.* 37, 48–74.
Brandstätter, E., Gigerenzer, G., and Hertwig, R. (2006). The priority heuristic: choices without tradeoffs. *Psychol. Rev.* 113, 409–432.
Brandstätter, E., Gigerenzer, G., and Hertwig, R. (2008). Postscript: rejoinder to Johnson et al. (2008) and Birnbaum (2008). *Psychol. Rev.* 115, 289–290.
Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–291.
Regenwetter, M., Dana, J., and Davis-Stober, C. (2010). Testing transitivity of preferences on two-alternative forced choice data. *Front. Psychol.* 1:148. doi: 10.3389/fpsyg.2010.00148
Regenwetter, M., Dana, J., and Davis-Stober, C. P. (2011). Transitivity of preferences. *Psychol. Rev.* 118, 42–56.
Tversky, A. (1969). Intransitivity of preferences. *Psychol. Rev.* 76, 31–48.
Tversky, A., and Kahneman, D. (1992). Advances in prospect theory: cumulative representation of uncertainty. *J. Risk Uncertain* 5, 297–323.

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# The stability of preferences – a social-cognition view

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Attitudes guide behavior. The social-cognitive approach to decision-making has been building on this assumption for almost a century (Allport, 1935). In this field, the model of reasoned action (Fishbein and Ajzen, 1974) was probably the most influential advance in describing the relation between attitudes and behavior. Accordingly, attitudes are the key predictor of behavioral intentions. They are formally described as a function of a linear integration of evaluations and probabilities (beliefs). The attitudinal part of the model dovetails with the subjectively expected-utility (SEU) approach to risky decision-making (Edwards, 1954). In line with attitude–behavior models, preferences are stable attitudes toward behaviors.

After its formation, an attitude can be stored in memory in association with the attitude object (e.g., Fazio, 1990; Wilson et al., 2000; Betsch, 2005). Attitude storage opens the path to stability. If a person re-encounters an attitude object, she can look up her attitude in memory and use it for subsequent judgment and choice. Individual preferences should be stable to the extent that the person relies on stored attitudes.

This so-called "file-drawer" notion (Wilson and Hodges, 1992), however, has been challenged by empirical evidence. Attitudinal responses in risky and non-risky choice domains were shown to be susceptible to a variety of task conditions. Krosnick and Schuman (1988) showed that response order, question wording and format systematically affect attitude judgments irrespective of their subjective importance, extremity, and certainty. In a similar vein, empirical violations of the axioms of decision theory challenged the notion that preferences are stable (e.g., framing effect, Tversky and Kahneman, 1981).

The *temporary construal approach*, in its extreme version, assumes that individuals *always* construct attitudes on the spot (Schwarz, 2000). In this view, stability is a function of the situation. In stable situations the sample of information (salient stimuli, activated knowledge) is invariant. Consequently, attitudinal judgments and behaviors are expected to be stable. If the situation changes, however, the sample of information changes as well and so will attitudes and behaviors. Accordingly, attitudes are transient constructions. Therefore, preferences cannot be stable.

The focus on variability, however, is prone to yield an un-representative picture of human behavior. Numerous examples of behavioral rigidity can be cited, both from everyday observation and controlled studies. Individuals regularly obey norms, repeat their routines, and fancy the same things two days in a row. Correspondingly, there is a bulk of psychological research demonstrating stability, especially in the field of learning. In their famous demonstrations of the *Einstellung-Effect*, Luchins and Luchins (1959) showed that only a few implementations of a problem-solving strategy suffice to induce a tendency to maintain the strategy even when less costly strategies are adequate. In recurrent risky choices, prior experience fosters maintenance of behavioral options (Betsch et al., 2001) and decision strategies (Bröder and Schiffer, 2006), even following changes in the pay-off structure that render the routine a maladaptive choice. A few behavior repetitions (less than 10) suffice to induce counter-intentional relapse errors[1] in subsequent choice (Betsch et al., 2004). In research on attitude–behavior models, Bentler and Speckart (1979), for instance, suggested including past behavior as an additional predictor in the Fishbein–Ajzen model.

How is it possible that there is evidence for both variability and stability in behavior? Many studies on variability employ tasks and judgment domains in which individuals lack behavioral experience. In contrast, studies on stability often assess behavior in recurrent tasks. It is widely acknowledged, however, that experience matters. Decisions based on experience yield different results from those in one-shot situations (e.g., Hertwig et al., 2004). Thus, one might conclude that preferences should be labile in new situations and stabilize with behavioral experience.

Note, however, that the behavioral invariance observed in recurrent and experienced-based situations is not a sufficient condition for inferring preference stability. According to attitude theory, preferential stability requires that the *attitude* remains stable and guides choice. Repetitive experience, however, could merely result in increasing the association between a stimulus and a response. If this were the case, we would expect stability in recurrent situations and variability when situations change in the sense that the learned stimulus is no longer present. Explaining stability in stable situations does *not* necessitate the assumption of a stable attitude because it is the stimulus situation and not the attitude that might induce stable responses. Stimulus-directed choice is likely to occur if a behavior has been repeated so frequently in the past that it has been "frozen into habit" (James, 1890/1950; Verplanken and Aarts, 1999). Habits are responses that are instantiated automatically upon recognizing the associated stimulus. Indeed, there is evidence that highly frequent behavior repetition can outperform attitudes and intentions (Ouellette and Wood, 1998). On the other hand, the fact that habits are implemented in a stimulus-directed fashion without involving goals and intentions (Wood and Neal, 2007) does not speak against the possibility that attitudes can also become stable with behavior repetition and may systematically guide *intentional* decisions.

Two conditions must be met to justify the assumption that repetition paves the way to preference stability. First, previous behavior must increase the association between an attitude and an object. Accordingly, response latencies for attitude judgments

[1]A relapse error occurs if the actor performs a routine behavior against his or her intention to deviate from this routine.

were found to decrease with increasing frequency of prior activation of the attitude object (Fazio et al., 1986). Most important, studies using a conceptual priming technique show that activation of an attitude object can result in automatic activation of attitudes (Fazio et al., 1986).

Second, if it is truly the attitude that can guide behavior in intentional decisions, than we should observe a generalization of the preferred behavior to conditions that deviate from those under which the behavior has been learned. Generalization should occur especially for frequent compared to infrequent behaviors because in the former the behavior–attitude association is strong. Such transfer effects could not easily be accounted for by a stimulus–response model.

The following demonstration provides evidence of a generalization of strong attitudes. Sixty undergraduates from various majors at the University of Erfurt received vignettes involving food choices in everyday settings. Half of the behaviors were frequently performed in the past, such as drinking coffee or tea at breakfast. Others were infrequent such as foreign meals offered on the exchange-students day. Measures of attitudes toward the alternatives (nine-point rating scale: dislike–like) and choices were assessed twice with a 2-week delay in between. At the second assessment, participants were randomly assigned to two conditions. Half of the participants received descriptions of new situations mostly atypical of everyday settings. The other half received the same descriptions that they were exposed to at the first assessment. Even though the situations differed between the two conditions, the set of alternatives was identical.

Mean correlations ($r$) between attitudes and choices over vignettes were generally above 0.50 and significant – both within and between the two times of measurement. First-time attitudes and choices were equally strongly associated with second-time choices. These results indicate that attitude–choice relations were quite strong and stable over time. More revealing, however, are the results from a comparison of *old* and *new* situations. For *frequent* behaviors, the correlations between the first-time attitudes and choices and second-time choices were substantially larger in new (mean $r = 0.90$) as compared to old situations (mean $r = 0.66$). For infrequent behaviors, a reverse pattern for old ($r = 0.70$) and new situations ($r = 0.59$) was obtained.

Not only the predictive power of past choices but also the predictive power of attitudes seems to stabilize with behavior repetition over time and situations. Generalization indicates that behavior repetition appears to stabilize preferences beyond creating mere stimulus–response associations. Hence, one might conclude that stability in preferences is a function of behavioral repetition and storage processes.

Attitude research, however, suggests that consolidation of attitude–behavior relations in memory is *not* a sufficient condition for stability because the *cognitive processes* at the time of decision matter as well. Individuals can use different styles of thinking involving more or less deliberative effort (Evans, 2008). Economists often assume that individuals must think carefully to arrive at good (rational) decisions (Hertwig and Ortmann, 2001, for a discussion). Thus, violations of the axioms of rationality (e.g., preference reversals) may be attributed to shallow thinking under flawed incentive structures.

Does thorough thinking foster stability? When considering theorizing and empirical results from attitude research, one arrives at the *opposite* prediction. In his MODE-model, Fazio (1990) assumes that reliance on stored attitudes increases the *less* a person is motivated and able to think carefully about the decision. Under high motivation and in the absence of constraints, the individual is expected to engage in a *new* assessment of risks and benefits. In line with this prediction, individuals have been found to change preferences when "thinking too much" (Wilson and Schooler, 1991). Accordingly, individuals should be more likely to rely on prior attitudes if they make decisions without investing much cognitive effort (Betsch and Glöckner, 2010).

From the social-cognition approach, we can conclude that preferences (attitudes) can indeed stabilize and yield stability in judgment and decision-making under certain conditions. Stability is probably a joint function of memory and judgment processes. We should expect stability to increase with behavior repetition in the past and when individuals do not think much before making their decisions.

## REFERENCES


Allport, G. W. (1935). "Attitudes" in *Handbook of Social Psychology*, ed. C. Murchison (Worcester, MA: Clark University Press), 798–844.

Bentler, P. M., and Speckart, G. (1979). Models of attitude-behavior relations. *Psychol. Rev.* 86, 452–464.

Betsch, T. (2005). "Preference theory – an affect-based approach to recurrent decision making" in *The Routines of Decision Making*, eds T. Betsch and S. Haberstroh (Mahwah, NJ: Lawrence Erlbaum), 39–65.

Betsch, T., and Glöckner, A. (2010). Intuition in judgment and decision making: extensive thinking without effort. *Psychol. Inq.* 21, 1–16.

Betsch, T., Haberstroh, S., Glöckner, A., Haar, T., and Fiedler, K. (2001). The effects of routine strength on information acquisition and adaptation in recurrent decision making. *Organ. Behav. Hum. Dec.* 84, 23–53.

Betsch, T., Haberstroh, S., Molter, B., and Glöckner, A. (2004). Oops, I did it again – relapse errors in routinized decision making. *Organ. Behav. Hum. Dec.* 93, 62–74.

Bröder, A., and Schiffer, S. (2006). Adaptive flexibility and maladaptive routines in selecting fast and frugal decision strategies. *J. Exp. Psychol. Learn. Mem. Cogn.* 32, 904–918.

Edwards, W. (1954). The theory of decision making. *Psychol. Bull.* 51, 380–417.

Evans, J. S. B. T. (2008). Dual-processing accounts of reasoning, judgment, and social cognition. *Annu. Rev. Psychol.* 59, 255–278.

Fazio, R. H. (1990). Multiple processes by which attitudes guide behavior: the MODE model as an integrative framework. *Adv. Exp. Soc. Psychol.* 23, 75–109.

Fazio, R. H., Sanbonmatsu, D. M., Powell, M. C., and Kardes, F. R. (1986). On the automatic activation of attitudes. *J. Pers. Soc. Psychol.* 50, 229–238.

Fishbein, M., and Ajzen, I. (1974). Attitudes towards objects as predictors of single and multiple behavioral criteria. *Psychol. Rev.* 81, 59–74.

Hertwig, R., Barron, G., Weber, E. U., and Erev, I. (2004). Decisions from experience and the effects of rare events in risky choice. *Psychol. Sci.* 15, 534–539.

Hertwig, R., and Ortmann, A. (2001). Experimental practices in economics: a methodological challenge for psychologists. *Behav. Brain Sci.* 24, 383–451.

James, W. (1890/1950). *The Principles of Psychology*, Vol. 1. New York: Dover.

Krosnick, J. A., and Schuman, H. (1988). Attitude intensity, importance, and certainty and susceptibility to response effects. *J. Pers. Soc. Psychol.* 54, 940–952.

Luchins, A. S., and Luchins, E. H. (1959). *Rigidity of Behavior. A Variational Approach to the Effect of Einstellung.* Eugene: University of Oregon Press.

Ouellette, J. A., and Wood, W. (1998). Habit and intention in everyday life: the multiple processes by which past behavior predicts future behavior. *Psychol. Bull.* 124, 54–74.

Schwarz, N. (2000). AGENDA 2000 – Social judgment and attitudes: warmer, more social, and less conscious. *Eur. J. Soc. Psychol.* 30, 149–176.

Tversky, A., and Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science* 211, 453–458.

Verplanken, B., and Aarts, H. (1999). Habit, attitude, and planned behavior: is habit an empty construct or an interesting case of goal-directed automaticity? *Eur. Rev. Soc. Psychol.* 10, 101–134.

Wilson, T. D., and Hodges, S. D. (1992). "Attitudes as temporary constructions" in *The Construction of Social*

*Judgment*, eds L. L. Martin and A. Tesser (Hillsdale, NJ: Erlbaum), 37–65.

Wilson, T. D., Lindsey, S., and Schooler, J. W. (2000). A model of dual attitudes. *Psychol. Rev.* 107, 101–126.

Wilson, T. D., and Schooler, J. W. (1991). Thinking too much: introspection can reduce the quality of preferences and decisions. *J. Pers. Soc. Psychol.* 60, 181–192.

Wood, W., and Neal, D. T. (2007). A new look at habits and the habit-goal interface. *Psychol. Rev.* 14, 843–863.

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# Constructing preferences in the physical world: a distributed-cognition perspective on preferences and risky choices

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Psychological research has firmly established that risk preferences are transient states shaped by past experiences, current knowledge, and feelings as well as the characteristics of the decision environment. We begin this article with a brief review of evidence supporting this conception as well as different psychological theories explaining how preferences are constructed. Next, we introduce the distributed perspective on human cognition and show how it may offer a promising framework for unifying seemingly incompatible accounts. We conclude by suggesting new directions for better capturing the essence of preference construction in laboratory research.

## ON THE PSYCHOLOGY OF HUMAN PREFERENCES AND RISKY CHOICES

Psychologists have long assumed that core cognitive processes such as memory, perception, and attention are inherently *constructive* – they are the product of the content of thoughts and the situation within which people are embedded when they think (Bartlett, 1932; Neisser, 1967). Risk preferences are no exception. As Lichtenstein and Slovic (2006, p. 1) put it: "in many situations we do not really know what we prefer; we must construct our preferences as the situation arises." Scholars often situate the origins of the concept of preference construction in Simon's (1956, 1990) focus on the bounded capacities of the human information-processing system on the one hand, and the shaping properties of the environment within which decisions are made, on the other. In Simon's words "Human rational behavior … is shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor" (Simon, 1990, p. 7).

The notion that preferences are constructed is supported by a body of evidence that is both vast and varied. Lichtenstein and Slovic's (1971) work on *preference reversals* demonstrated the key role of response mode – bidding for a bet vs. choosing a bet – in shaping preferences for risky gambles. The work of Tversky and Kahneman's (1981) on *choice framing* illustrated how the superficial framing of the description of options can cause a reversal in risk preferences – from risk-seeking preferences in a choice between options framed with losses to risk-averse preferences when the same choice is framed with gains. More recently research has shown that preferences may also depend on how outcomes are experienced – either as a descriptive summary, or through actual sampling (Hertwig et al., 2004). Meanwhile, the impact of transient states such as affect and feelings on risk judgments (Slovic et al., 2002) further corroborates the conception of preferences as situated in time and space.

Several theories have been proposed to explain how preferences and associated decisions may be constructed. Some conceive preference construction as resulting from the impact of the environment on individuals' strategy choice or representations. The *ecological approach* (e.g., Brighton and Todd, 2009) proposes that the mind is endowed with an "adaptive toolbox" containing purpose-built simple decision heuristics that exploit the structure of the information in the immediate environment. The *choice goals framework* (Bettman et al., 1998) also assumes that individuals possess a repertoire of choice heuristics, acquired through experience or training. From these perspectives, an environment with a particular information structure will shape cognition by inviting the application of the decision heuristic that is most adapted to this structure. Similarly, accounting for risky choice framing, *prospect theory* (Kahneman and Tversky, 1979) suggests that the environment affects risk preferences and decisions through its impact on individuals' representations – as opposed to its impact on strategy selection – as decisions outcomes may be represented as gains or losses, depending on the reference point made salient in the task environment. Meanwhile, other theories characterized preference construction as an internal process where the role of the individual's immediate environment is less prominent. Svenson's (1996) differentiation and consolidation (DiffCon) theory posits that construction occurs through cycles of alterations of the decision task's mental representation in order to single out the alternative of choice. Search for dominance structure (SDS) theory (Montgomery, 1998) offers a similar conception where preferences are assumed to arise from the restructuring of the mental representation of attribute information to identify the dominant alternative. Svenson (1996) does note that context and decision structure may influence the decision rules that are elicited. Montgomery (1998) adds that "individual may also intervene *in* the external world to increase the support for the to-be-chosen alternative" (p. 287, emphasis added) but he does not specify what those interventions may be, what might be intervened *upon*, or by which mechanisms such interventions may result in increased support.

While these theories stress important features of the constructive process of preferences, we also believe that they offer an incomplete view of this process because they omit an essential aspect of how people may naturally construct their preferences: through their *actions on* their immediate environment. In the next section of this article, we present a theoretical framework that places interactivity at the forefront of efforts to understand choice preferences.

## BEYOND SITUATED COGNITION: COGNITION DISTRIBUTED

A group of cognitive scientists, initially drawn from cognitive ergonomics and anthropology, have lobbied for a shift in the main unit of analysis to understand thinking (e.g., Hollan et al., 2000). They reject a traditional model of the mind where cognition is sandwiched between perceptual inputs and behavioral outputs (to adapt Hurley, 2001). Instead they argue that cognition is the product of a distributed system that reflects the dynamic meshwork of resources internal to the reasoner (such as cognitive capacities, acquired knowledge) as well as resources external to the reasoner (such as artifacts, people, cultural beliefs; Kirsh, 2009, 2010; Hutchins, 2010). A key notion in the systemic perspective is that people interact with external resources to augment and facilitate thinking. From a distributed-cognition perspective, thinking is the product of embodied and embedded mental and physical activities. In other words, people do not just "*think* with their heads," they also "*think* with their eyes and hands" in an environment that affords interaction. This results in an extended cognitive system (Wilson and Clark, 2009), akin to an ecological niche (cf. Laland et al., 2000) enabling people to exceed the capacities of their unaided, non-extended mind.

People act upon their environment when they think, and more specifically when they evince a preference, in a rich and varied manner; yet this activity is rarely the focus of research. People, generally, do not choose their homes or their cars from written descriptions. Rather, they walk in potential flats, project and sketch furniture placement, open and close wardrobes, sit on the terrace to help simulate what it would be like to live in the place. In other words, they do not only adapt to their environment, they actively shape, manipulate, and interact with it to support their decision-making.

The distributed perspective has been the subject of ethnographic analysis "in the wild" (Hutchins, 1995), but it can also guide more controlled experimental work (Fioratou and Cowley, 2009; Weller et al., in press). For example, we recently examined performance on matchstick algebra problems which present participants with a false algebraic equation made of matchsticks and require them to move one matchstick to form a true equation (Knoblich et al., 1999). Adopting a distributed-cognition perspective, we compared performance on the traditional paper-and-pencil version of the task with performance in an interactive version where participants could physically manipulate the matchsticks, using a modifiable, three-dimensional, physical presentation of the equation. Participants in the interactive group were significantly more likely to achieve insight to transform these expressions into true equations. Moreover, whereas numeracy predicted performance in the paper-and-pencil group, performance was best predicted by visuo-spatial reasoning skills in the interactive group. These results suggest that different types of resources and skills were recruited in the interactive and non-interactive versions of the task, respectively.

The distributed-cognition perspective may also offer a novel way to conceive the role of the environment in the construction of preferences. The theoretical frameworks reviewed earlier assume that the environment shapes cognitive activity. In experiments used to test these approaches, however, the environment is often presented in a two-dimensional, fixed presentation akin to the non-interactive version of the matchstick algebra task, offering linguistic or numerical information that is presented in essentially inflexible and intangible formats. These environments severely limit individuals' natural tendency to think with their eyes and hands. The distributed-cognition perspective could offer a new window onto the process of preference construction, focusing on the coupling between people's cognition and the strategic and opportunistic manipulation of the information populating their immediate physical space. As Weller et al.'s (in press) study illustrates, adopting a distributed perspective on cognition does not necessitate studying cognitive activities in naturalistic settings. In fact, we believe that the potential of this approach resides in its promise to better capture the essence of cognitive processes in general, and preference construction in particular, within laboratory settings.

Adopting a distributed-cognition perspective also highlights a potentially invalid assumption underpinning alternative accounts of preference construction, such as SDS theory (Montgomery, 1998) and the DiffCon theory (Svenson, 1996) reviewed above – and more generally, numerous theories accounting for higher level cognitive processes – namely, the assumption that the *mental restructuring* of a rigid presentation of the informational landscape is equivalent to the *physical restructuring* of this landscape, in the individual's immediate environment. It is not: an inflexible physical problem presentation exerts gravity on people's effort to depart from and transform their representation of the information; whereas a dynamic one may better support the development of a productive representation of the problem information.

Concretely, better understanding how preferences may be constructed in the physical world will involve designing experimental settings where participants are no longer limited to alter the information presented to them mentally. This, we surmise, will lead to a revision of the amount of information that people are actually capable of computing when constructing preferences. For example, a canonical representation of the information in choice framing tasks such as the Asian Disease problem (Tversky and Kahneman, 1981) requires taking into account all outcomes of concurrent decisions. Such a bias-free representation has been previously ruled out as psychologically implausible, assuming that it would exceed human computational capabilities (Kahneman and Tversky, 1984). Maule and Villejoubert (2007) surmised that participants might instead mentally switch between a gain-framed representation and a loss-framed representation, in a similar manner to the perspective-switching occurring when people are presented with ambiguous figures such as the Necker cube. Choice behavior would then be determined by the dominant representation at the moment of choice. Taking a distributed-cognition approach to study choice framing, one could use playing cards presenting a positive or negative outcome associated with each of two alternatives. Probabilities of outcomes would be presented as the relative proportion of positive and negative outcomes. This would enable participants to manipulate, spread, arrange and rearrange the cards, and perhaps contrast losses and gains while constructing their preference. Importantly, rather than constrain thinking, the manipulability afforded by the material presentation of the information would instead support – if not augment – people's computational abilities. In such a situation, the mental switch of focus between a gain-framed and a loss-framed representation (Maule and Villejoubert, 2007) could then be supported by the physical presentation of the information and thus, considerably reducing the mental efforts required for switching focus. Moreover, this would make the process of restructuring directly accessible to the researcher, through the observation and coding of the actions and eye-gazes executed by the decision-makers.

To conclude, Simon's (1956, 1990) emphasis on the major shaping role played by the environment within which decisions are made has often been used to explain how preferences are constructed. Simon's argument has often been summarized as focusing on the "interaction" between individuals' mental activities and their immediate environment (e.g., Brighton and Todd, 2009, p. 339; Lichtenstein and Slovic, 2006, p. 23; Bettman et al., 1998, p. 187). However, interactivity as such never figures in either Simon's (1956, 1990) account or in subsequent theoretical efforts. Some have developed theories explaining how decision-makers may select choice heuristics that are *fitted to* the structure of the environment. Others have stressed the importance of the mental restructuring of the information in preference construction. In this article we sought to illustrate how neither approaches can fully account for the essence of preference construction as it may occur in natural settings. We propose that this is because past research has neglected an important aspect of cognition – viz., how interactions with the world may influence and support mental processes. Whether, under what conditions, and by which processes, freeing up decision-makers' hands may indeed affect the way they construct their preferences, may thus prove to be an important new avenue for research.

## REFERENCES


Bartlett, F. C. (1932). *Remembering*. Cambridge: Cambridge University Press.

Bettman, J. R., Luce, M. F., and Payne, J. W. (1998). Constructive consumer choice processes. *J. Consum. Res.* 25, 187–217.

Brighton, H., and Todd, P. M. (2009). "Situating rationality: ecologically rational decision making with simple heuristics," in *The Cambridge Handbook of Situated Cognition*, eds P. Robbins and M. Aydede (New York, NY: Cambridge University Press), 322–346.

Fioratou, E., and Cowley, S. (2009). Insightful thinking: cognitive dynamics and material artifacts. *Pragmat. Cogn.* 17, 549–572.

Hertwig, R., Barron, G., Weber, E. U., and Erev, I. (2004). Decisions from experience and the effect of rare events in risky choice. *Psychol. Sci.* 15, 534–539.

Hollan, J., Hutchins, E., and Kirsh, D. (2000). Distributed cognition: toward a new foundation for human-computer interaction research. *ACM Trans. Comput. Hum. Interact.* 7, 174–196.

Hurley, S. L. (2001). Perception and action: alternate views. *Synthese* 129, 3–40.

Hutchins, E. (1995). *Cognition in the Wild*. Cambridge, MA: MIT Press.

Hutchins, E. (2010). Cognitive ecology. *Top. Cogn. Sci.* 2, 705–715.

Kahneman, D., and Tversky, A. (1979). Prospect theory: an analysis of decision under risk. *Econometrica* 47, 263–291.

Kahneman, D., and Tversky, A. (1984). Choices, values, and frames. *Am. Psychol.* 39, 341–350.

Kirsh, D. (2009). "Interaction, external representation and sense making," in *Proceedings of the Thirty First Annual Conference of the Cognitive Science Society*, eds N. A. Taatgen and H. V. Rijn (Austin, TX: Cognitive Science Society), 1103–1108.

Kirsh, D. (2010). Thinking with external representations. *AI Soc.* 25, 441–454.

Knoblich, G., Ohlsson, S., Haider, H., and Rhenius, D. (1999). Constraint relaxation and chunk decomposition in insight problem solving. *J. Exp. Psychol. Learn. Mem. Cogn.* 25, 1534–1555.

Laland, K. N., Odling-Smee, J., and Feldman, M. W. (2000). Niche construction, biological evolution, and cultural change. *Behav. Brain Sci.* 23, 131–175.

Lichtenstein, S., and Slovic, P. (1971). Reversals of preference between bids and choices in gambling decisions. *J. Exp. Psychol.* 89, 46–55.

Lichtenstein, S., and Slovic, P. (2006). "The construction of preference: an overview," in *The Construction of Preference*, eds S. Lichtenstein and P. Slovic (New York, NY: Cambridge University Press), 1–40.

Maule, J., and Villejoubert, G. (2007). What lies beneath: reframing framing effects. *Thinking Reasoning* 13, 25–44.

Montgomery, H. (1998). "Decision making and action: the search for a dominance structure," in eds *Personal Control in Action*, M. Kofta, G. Weary, and G. Sedek (New York, NY: Plenum Press), 279–298.

Neisser, U. (1967). *Cognitive Psychology*. New York, NY: Meredith.

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychol. Rev.* 63, 129–138.

Simon, H. A. (1990). Invariants of human behavior. *Annu. Rev. Psychol.* 41, 1–19.

Slovic, P., Finucane, M. L., Peters, E., and Macgregor, D. G. (2002). "The affect heuristic," in *Heuristics and Biases: The Psychology of Intuitive Judgment*, eds T. Gilovich, D. Griffin, and D. Kahneman (New York, NY: Cambridge University Press), 397–420.

Svenson, O. (1996). Decision making and the search for fundamental psychological regularities: what can be learned from a process perspective? *Organ. Behav. Hum. Decis. Process.* 65, 252–267.

Tversky, A., and Kahneman, D. (1981). The framing of decisions and the psychology of choice. *Science* 211, 453–458.

Weller, A., Villejoubert, G., and Vallée-Tourangeau, F. (in press). Interactive insight problem solving. *Think. Reason.*

Wilson, R. A., and Clark, A. (2009). "How to situate cognition: letting nature take its course," in *The Cambridge Handbook of Situated Cognition*, eds P. Robbins and M. Aydede (Cambridge: Cambridge University Press), 55–77.


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# Inherent individual differences in utility

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## 1 WHO KNOWS A UTILITY REPRESENTATION

Repeatedly it is alleged that this or that theory concerns a decision maker maximizing some utility function. But, as I have been at pains to discuss, the representation is not a creature of the decision maker but of the scientist studying the decision maker's behavior "The representation theorems go in only one direction: from behavioral and structural properties to numerical representations. The behavioral properties embody the scientific information that we, as scientists, have about the decision maker. It is the scientist, not the decision maker, who formulates both the properties (axioms) and the representation. The decision maker exhibits the behavior which, presumably, arises from some fairly complex neuronal processes…" (Luce, 2000, p. 25). This observation holds far more broadly than just in decision making.

## 2 UNIQUENESS OF THE REPRESENTATION

Uniqueness of representations is, of course, a very well trodden topic. The gist is that in addition to proving a representation theorem, one must also formulate a uniqueness theorem – how do the several representations relate? In most of the popular measurement theories, the uniqueness falls into one of Stevens' (1946, 1951) well known classification: nominal, ordinal, interval, log-interval, ratio, and absolute scales (see Krantz et al., 1971; Luce et al., 1990).

As I recently came to realize, when we are dealing with a preference weak order $\succsim$ and a binary operation $\oplus$, such as the concatenation of two sums of money, for which 0 money is an identity of $\oplus$ and $\oplus$ is commutative, associative, and monotonic in $\succsim$, things are not really quite as simple as has been long believed.

Recall that Hölder (1901) proved in this context the existence of an additive representation

$$\begin{aligned}\psi(x\oplus y) &= \psi(x\oplus 0)+\psi(0\oplus y) \\ &= \psi(x)+\psi(y),\end{aligned} \quad (1)$$

which is unique up to a ratio scale.

A century later it was recognized that, in the context of utility theory, we also have the interplay between value and risk, which means that multiplication as well as addition is in play. See, e.g., (3) below. So the mapping should be into $\langle \mathbb{R}, \geq, +, \times\rangle$, in which case the full set of polynomial (p-additive) representations are (see Luce, 2000, p.151, § 4.4.6)

$$\begin{aligned}&\psi(x\oplus y) \\ &= \psi(x)+\psi(y)+\delta\psi(x)\psi(y) \quad \delta=-1,0,1.\end{aligned} \quad (2)$$

Of course, $\delta = 0$ is Hölder's original solution. The other two are quite different in that they are absolute scales (see Luce, 2010a). Here is the reason: when $\delta \neq 0$, (2) is equivalent to

$$1+\delta\psi(x\oplus y) = \big(1+\delta\psi(x)\big)\big(1+\delta\psi(y)\big).$$

But this expression is not invariant under any transformation of $\psi$ other than the identity. The fact they are absolute scales has several important implications.

## 3 SOME IMPLICATIONS OF THE p-ADDITIVE REPRESENTATION

### 3.1 THREE TYPES OF PEOPLE

There are three inherently different types of people corresponding to their values of $\delta$. The following simple behavioral criterion to decide a particular person's type was reported by Luce (2010a).

Let $(x, p; y, 1-p)$ denote the gamble where $x$ occurs with probability $p$ and $y$ with probability $1-p$ and suppose, as is true in a great many theories of utility, that

$$\begin{aligned}U\big(x,p;y,1-p\big) &= U(x)W(p) \\ &\quad +U(y)W(1-p),\end{aligned} \quad (3)$$

where $\psi$ has been replaced in this context by $U$ for utility, $W$ is a strictly increasing subjective probability function, and $W(0) = 0$. Further, assume that

$$W(p)+W(1-p)=1. \quad (4)$$

Find the probability $p_{1/2}$ with subjective probability 1/2, i.e., such that for the representation (3) and for all $x > y$

$$\begin{aligned}\big(x,p_{\frac{1}{2}};y,1-p_{\frac{1}{2}}\big) \sim \big(y,p_{\frac{1}{2}};x,1-p_{\frac{1}{2}}\big) &\Leftrightarrow W(p_{\frac{1}{2}}) \\ &= \frac{1}{2}.\end{aligned} \quad (5)$$

I assume that $W(p) = p$ is satisfied for $p = 0$, $p = p_{1/2}$, possibly for $p = 1$, but not elsewhere. Note that it follows that relative to the line $f(p) = p$, the weighting function $W$ must be either S-shaped or inverse S-shaped. See Section 3.4 of Luce (2000) for a summary of empirical estimates which seem to agree with this prediction.

Then the criterion for $\delta$ is that for all $x > x' > y > y'$

$$\begin{aligned}&\delta = \begin{Bmatrix}1\\0\\-1\end{Bmatrix} \Leftrightarrow \\ &\big(x\oplus x', p_{\frac{1}{2}}; y\oplus y', 1-p_{\frac{1}{2}}\big)\begin{Bmatrix}\succ\\ \sim\\ \prec\end{Bmatrix} \\ &\big(x\oplus y, p_{\frac{1}{2}}; x'\oplus y', 1-p_{\frac{1}{2}}\big).\end{aligned} \quad (6)$$

Observe that under the ordering constraint on the consequences, the gamble on the left has a greater variance than the one on the right. For that reason, the three $\delta$ types are called, respectively, risk-seeking ($\delta = 1$), risk-neutral ($\delta = 0$), and risk-averse ($\delta = -1$). It would not surprise me that in the academic population, which is the source of many experimental respondents, risk-averse types will predominate except, perhaps, in schools of business.

It has yet to be shown empirically that this classification holds up in the population. But should it, one simply should not average data over people without, at the least, dealing with the three classes separately. Indeed, really only the $\delta = 0$ types should ever be averaged. Individual differences are important. This has significant implications – e.g., many behavioral economic experiments should be redone taking into account individual types (Luce, 2010b).

### 3.2 UTILITY FORMS OF RISK TYPES

Three forms of utility follow from (2) and (6): there exist positive constants α, κ, and λ such that

$$U(x)=\begin{Bmatrix} e^{\kappa x}-1 \\ \alpha x \\ 1-e^{-\lambda x} \end{Bmatrix} \Leftrightarrow \delta=\begin{Bmatrix} 1 \\ 0 \\ -1 \end{Bmatrix} \qquad (7)$$

(Luce, 2010a). Note that for $\delta = 1$, this function is bounded from below by $-1$ and unbounded from above, whereas for $\delta = -1$ it is unbounded from below and bounded by 1 from above.

### 3.3 INTERPERSONAL COMPARISONS OF UTILITY

Because the $\delta \neq 0$ scales are absolute, interpersonal comparisons become meaningful, although for a mix of $-1$ and 1 types, only in the common interval $(-1,1)$ (Luce, 2010a). No such comparisons can be made involving risk-neutral types of people. If correct, this makes sense of the fact that classical utility theorists have found interpersonal comparisons impossible (e.g., Robbins, 1938; Harsanyi, 1977; Elster and Roemer, 1991; Hammond, 1991; Binmore, 2009) although most of us intuit that we regularly make such comparisons. And just how many of us are risk-neutral?

### 3.4 PSYCHOPHYSICAL SCALING IN GENERAL

As I have thought more about subjective intensity scales, I have come to realize that many other attributes of subjective intensity closely resemble the utility theory of risk except that most are defined only on the non-negative real numbers (Luce, under review). Indeed, the only exceptions that I know of involve what can be called binary senses that involve the close interaction of the two ears and of the two eyes. The binary theory coupled with certain loudness and brightness data simply rule out the two $\delta \neq 0$ cases.

Thus, when we ask a respondent to match subjective intensities of one modality to those of another modality, then, because of the three values of δ arise for all but the binary attributes, we get a complex of predicted results (Luce, under review, Table 1). This fact suggests an extensive experimental program to be done.

## 4 CLOSING REMARKS

I have made a strong claim here, namely, that a slight mathematical oversight – mapping just into addition when, for other theoretical reasons, multiplication is also involved – has put us on a misguided course for over a century. And that course may, in a number of ways, have been scientifically misleading.

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## REFERENCES

Binmore, K. (2009). "Interpersonal comparison of utility," in *Oxford Handbook of the Philosophy of Economics*, Chapter 20, eds H. Kincaid and D. Ross (New York, NY: Oxford University Press), 540–559.

Elster, J., and Roemer, J. (eds). (1991). *Interpersonal Comparisons of Well-Being*. London: Cambridge University Press.

Hammond, P. (1991). "Interpersonal comparisons of utility: why and how they are and should be made," in *Interpersonal Comparisons of Well-Being*, eds J. Elster and J. Roemer (London: Cambridge University Press), 200–254.

Harsanyi, J. (1977). *Rational Behavior and Bargaining Equilibrium in Games and Social Situations*. Cambridge: Cambridge University Press.

Hölder, O. (1901). Die Axiome der Quantität und die Lehre vom Mass. *Ber. Verh. Kgl. Sächsis. Ges. Wiss. Leipzig Math.-Phys. Classe.* 53, 1–64.

Krantz, D. H., Luce, R. D., Suppes, P., and Tversky, A. (1971). *Foundations of Measurement*, Vol. I, Reprinted 2007. New York: Academic Press.

Luce, R. D. (2000). *Utility of Gains and Losses*. Mahwah, NJ: Erlbaum

Luce, R. D. (2010a). Interpersonal comparisons of utility for 2 of 3 types of people. *Theory Decis.* 68, 5–24.

Luce, R. D. (2010b). Behavioral assumptions for a class of utility theories: a program of experiments. *J. Risk Uncertain.* 41, 19–27.

Luce, R. D., Krantz, D. H., Suppes, P., and Tversky, A. (1990). *Foundations of Measurement: Vol. III. Representations, Axiomatization, and Invariance*, Reprinted 2007. San Diego: Academic Press.

Robbins, L. (1938). Interpersonal comparisons of utility: a comment. *Econ. J.* 48, 635–641.

Stevens, S. S. (1946). On the theories of scales of measurement. *Science* 103, 677–680.

Stevens, S. S. (ed.). (1951). *Handbook of Experimental Psychology*. New York: Wiley.

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