Does Memory Mediate Susceptibility to Cognitive Biases? Implications of the Decision-by-Sampling Theory

Belinda Bruza, Matthew B. Welsh & Daniel J. Navarro
({belinda.bruza@student., matthew.welsh@, daniel.navarro@}adelaide.edu.au)
University of Adelaide, SA 5005, Australia

Abstract

Stewart, Chater and Brown's (2006) decision-by-sampling theory proposes that people make decisions about everyday events by drawing samples of "similar" events from memory and comparing them to the event in question. Classic gains-versus-losses framing effects emerge naturally from the theory, along with a number of other decision-making phenomena. In this paper, we note that since these biases are treated as memory-related, and there are empirically observed individual differences in both memory and susceptibility to bias, the two might be expected to be related. Specifically, better memory should reduce overconfidence but, somewhat counterintuitively, strengthen framing effects. To test this, we measured working and retrieval memory for 60 undergraduates, and compared these to their susceptibility to each bias. Although the data collected displayed the usual decision-making effects, no relationship was found between memory and either bias once covariates were controlled for.

Keywords: decision making; bias; cognitive processes; overconfidence; framing.

The idea that people make decisions by sampling information from the environment or memory has a long history in cognitive science, having been applied to visual perception (Vickers, 1979), memory (Ratcliff, 1978) and categorization (Nosofsky & Palmeri, 1997) among other things, and remains the dominant explanation for various phenomena associated with decision times (see Luce, 1986). More recent papers have developed sampling-based explanations of classic judgment and decision-making behavior (e.g., Gigerenzer & Goldstein, 1996; Lee & Cummins 2002; Stewart, Chater & Brown, 2006). Stewart et al (2006), in particular, propose a specific sampling approach (which, perhaps confusingly, they just call "decision-by-sampling", or DbS) that explains gain-versus-loss framing effects and hyperbolic intertemporal discounting curves by reference to the underlying environmental/memory structure from which samples are drawn, in a manner that is loosely consistent with Anderson's (1990) rational approach to cognition.

In this paper, we note that, within the DbS framework, there are two quite different methods by which biases can be produced, and from which experimental predictions can be obtained. We then present results that suggest that, when cast in a strong form that incorporates individual differences, predictions consistent with DbS are not met.

Two Kinds of Bias

Framing: A Distributional Bias. Kahneman and Tversky (1979) proposed that subjective value functions relating an objective value to a psychological prospect are non-linear, with two key properties. The first is the decreasing utility of both losses and gains – that is, as monetary values increase in size, their value to a person does not increase in the same linear fashion. To take a simple example, winning \$1 million would make an enormous difference to the lives of most people but the changes resulting from winning \$2 million are not twice as great. Their second observation was that, for most people, loss functions are steeper than gain functions. That is, a loss of \$*x* is worse than a gain of \$*x* is good. Thus, losses weigh more heavily in people's minds.

As a consequence of these properties, people can show preference reversals when an option is described in terms of a gain, as opposed to in terms of a loss: people are risk-seeking for losses, but risk-averse for gains. This can be seen in Figure 1, which shows the typical pattern of subjective value functions: steeper for losses than gains and decreasing utility. So a gain of \$100, due to decreasing utility, is not twice as valuable as a gain of \$50. In contrast, a \$100 loss is not twice as *bad* as a \$50 loss and so a 50% chance of a \$100 loss is *better* than a certain \$50 loss. This effect has been repeatedly shown across monetary amounts and across domains as dissimilar as oil spill cleanup options (Pieters, 2004).

DbS proposes an explanation for this effect that does not require explicit value functions. Instead, to evaluate an option, people draw a *decision sample* of values from memory of "similar" options. The current value is then ranked within the decision sample to determine its relative value amongst these, as illustrated in Figure 2. The impact of the real world on the process is in determining the distribution of losses or gains from which the decision sample for any particular judgment is generated; that is, the values that have been seen in similar contexts to the current judgment. Stewart et al (2006) present data suggesting that in everyday experience, people tend to gain money in large chunks (e.g., paychecks) but lose money in smaller chunks (e.g., buying coffee). The key point is that the cumulative distributions produce shapes similar to prospect curves, but it is worth noting that if framing does rely on real-world distributions, it might explain why the framing effect does not always replicate when using questions about goods other than money (Rönnlund, Karlsson, Laggnäs, Larsson, & Lindström, 2005; Wang, 1996). If the distributions of

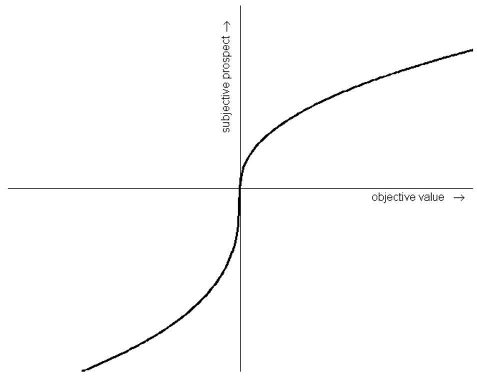

Figure 1: An example of a subjective value function, as described by prospect theory.

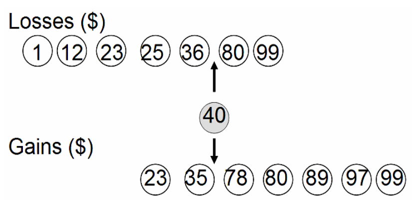

Figure 2: Utility of $40 evaluated against example decision samples of monetary gains and losses.

losses and gains for goods of these types differ from those for money, decision samples drawn from these might well lead to effects that differ from the classic framing effect.

DbS thus proposes that framing exists "in the distributions". Now, since the shape of the rank function is embedded in a real world distribution, it will be estimated much more accurately by larger samples: the gains versus losses distinction will appear *sharper* as more samples are collected. In short, the framing effect should be *stronger* when the decision sample is larger.

Overconfidence: A Sampling Bias. The overconfidence bias is the tendency to overestimate the accuracy of judgments (Lichtenstein, Fischhoff, & Phillips, 1982). Typically, when asked to provide a rating of their own performance or some analogue of a confidence interval, people tend to show more confidence than is warranted. Although Stewart et al (2006) do not discuss the application of DbS to confidence, sampling-based approaches have frequently been applied to confidence ratings (e.g., Vickers 1979, Merkle & Van Zandt 2006). For the current purposes, we are interested in the estimation of confidence intervals, which are commonly used in applied settings.

If decisions are made using a sample drawn from memory, it seems likely that any confidence range is estimated from the statistics of this sample. However, since small samples consistently underestimate the variability in the distribution, decisions based on simple sample statistics (the core proposal in DbS) will naturally produce overconfident predictions, an effect expected to be strongest when the decision sample is small.

Predicting Individual Differences

Motivated by the applied problem of needing to explain individual differences in cognitive bias, we develop a test of a slightly extended version of DbS. In the previous discussion we briefly outlined how DbS accounts for the shape of the value function for a *particular* person. A logical extension of DbS would propose that variability in memory processes should be reflected in a corresponding variability in the strength of framing and overconfidence effects. That is, people with better memories should be able to draw larger decision samples, leading to decreased overconfidence but increased susceptibility to framing. This implication, though not explicitly made by Stewart et al. (2006), follows naturally from the theory. Of course, as Stewart et al. (2006) note, there are a range of other factors that can alter the size and composition of the decision sample. As a result, the empirical question of whether individual differences in sampling from memory are strong enough to produce individual differences in cognitive bias (as per the extended DbS theory) is an open one, and one of considerable applied value. Accordingly, it is this extended "DbS-like" account of individual variability with which we are concerned.

Method

Participants

Sixty undergraduate psychology students at the University of Adelaide (15 males and 45 females), aged from 18 to 28 (M = 19.6, SD = 2.1) participated for course credit.

Materials

Risky-Choice Framing Tasks. Ten purpose-designed, self-report risky-choice framing tasks modeled on Tversky and Kahneman's (1981) study were used to measure framing susceptibility. The task involved five pairs of questions, each with a different type of 'good' at stake: human lives, money, objects, animals or communities. While the cover story varied between members of the same pair, the type of goods and numerical outcomes of the options remained the same. This enabled a within-subjects manipulation where a participant saw different questions regarding the same type of goods in both positive and negative frame conditions. A framing effect was assumed to occur if participants switched their preference between equivalent questions in the negative and positive versions. However, such a manipulation confounds the cover story with the framing effect, so half of the participants saw the same set of questions, with the framing reversed in all ten cases (see Table 1). This allows both simple tests that the different versions of the cover stories are not the source of any effect and a more sophisticated approach in which effects of frame and version are disambiguated, along with any interactions, using mixed models (discussed later).

Table 1. Framing of questions by group.

Question	1a	1b	2a	2b	3a	3b	4a	4b	5a	5b
Group 1	+	–	+	–	+	–	+	–	+	–
Group 2	–	+	–	+	–	+	–	+	–	+

Table 2: Percentage of participants choosing the 'risky option' on positive and negative framing tasks.

Scenario		**% Positive**	**% Negative**
Human Life	Nuclear Accident	46.7	53.3
	Building Collapse	56.7	70.0
Money	Insurance	6.7	33.3
	Investment	33.3	63.3
Objects	Manuscripts	16.7	23.3
	Statues	23.3	30.0
Animal	Cattle	13.3	56.7
	Penguins	23.3	36.7
Community	Villages	43.3	53.3
	Towns	40.0	50.0

Overconfidence. A 20-item questionnaire was used to assess overconfidence, modeled on Capen's (1976) approach, requiring participants to set confidence intervals (an elicitation method common in the oil and gas industry). Items were trivia questions such as "*How many countries are there in Europe?*"; participants providing a low and high guess (i.e., a range) in which they were 90% confident the actual answer lay. If such ranges are well-calibrated, then the number of ranges including the true answer should follow a Binomial(20,0.9) distribution. Additionally, in order to obtain confidence ratings as well as confidence intervals, participants indicated how knowledgeable they felt about the item on a 3-point scale: hard (*"absolutely no idea"*), medium (*"had a vague idea"*) and easy ("*I felt that I knew"*).

Memory. Human memory is not homogeneous, and although Stewart et al (2006) do not comment on which processes may be involved in the construction of a decision sample, it seems clear that working memory (Miller, 1956) and retrieval fluency (Mather & Woodcock, 2001) should play a role – that is, the abilities to retrieve items from long term store and to hold them in mind for comparison. Accordingly, retrieval fluency was measured via Test 12 of the Woodcock-Johnson III (Woodcock, McGrew, & Mather, 2001), and working memory capacity was measured via the Backward Digit Span task of the Digit Span subtest from the WMS-III (Wechsler, 1997).

Intelligence. Previous findings also indicate that individuals with higher intelligence are less susceptible to framing (Stanovich & West, 1998) and overconfidence (Pallier et al., 2002) and, given that performance on tests of mental ability (including memory) tend to correlate (Deary, 2001), tests of fluid (Gf) and crystallized (Gc) intelligence were included as covariate controls to ensure that any

Table 3: Model effects estimated via GEE methods, for five risky-choice framing task pairs.

Scenario		**Wald $\chi^2(1)$**	***p***
Human	Frame (F)	2.24	.14
	Version (V)	**3.89**	.05
	F × V	.12	.73
Money	Frame (F)	**12.82**	<.001
	Version (V)	**12.82**	<.001
	F × V	.43	.51
Object	Frame (F)	1.37	.24
	Version (V)	1.37	.24
	F × V	.01	.94
Animal	Frame (F)	**9.79**	<.01
	Version (V)	.02	.88
	F × V	3.13	.08
Community	Frame (F)	2.32	.13
	Version (V)	.26	.61
	F × V	.00	>.99

Note. Bold indicates significant effect at the .05 level. $N = 60$.

observed effect was due to differences in memory. Bors and Stokes' (1998) short form of Raven, Court and Raven's (1988a) Advanced Progressive Matrices (APM) was used as an indicator of Gf, while the Senior Form 1 of The Mill Hill Vocabulary Scale (Raven, Court, & Raven, 1988b) was used for Gc.

Procedure

The sample was divided into two groups (Group 1 and Group 2). Each participant received a single questionnaire composed of all the aforementioned tests other than the two memory measures, and one version of the risky-choice framing tasks (see Table 1). The order in which the measures were presented in each questionnaire was random, excepting that the risky-choice framing tasks were always separated by other measures (or instructions to see the researcher to complete a memory task).

Results

Framing Effects. As seen in Table 2, for each of the 10 framing questions, the proportion of participants selecting the risky option was greater when the question was negatively framed – a result that a sign test indicates is significant, $p<.001$. Across the whole data set, then, the framing effect is clearly apparent. However, as noted earlier, the study used a combination of within and between subjects conditions (with correlated frame and version assignments, as a matter of necessity) to allow a more detailed analysis to be conducted. Data in this format are efficiently handled using generalized estimating equations (GEEs; Liang & Zeger, 1986) to estimate the relevant marginal effects within the standard general linear model. Results are shown in Table 3.

The significance levels for the frame effects tended to be reasonable to good, ranging from $p = .24$ in the worst case to $p < .001$ in the best. In their own right, however, only the

Table 4: Spearman correlations between cognitive measures, framing and overconfidence scores.

	1	2	3	4	5	6
1 B. Digit Span		.24	.16	–.02	–.31*	–.19
2 Ret. Fluency			.45 **	–.01	–.13	–.14
3. Mill-Hill				.17	–.27*	–.31*
4 Ravens					–.13	–.21
5 Framing						.21
6 Overconf.						

Note: * = sig. at the .05 level.** = sig. at the .001 level. $N = 60$.

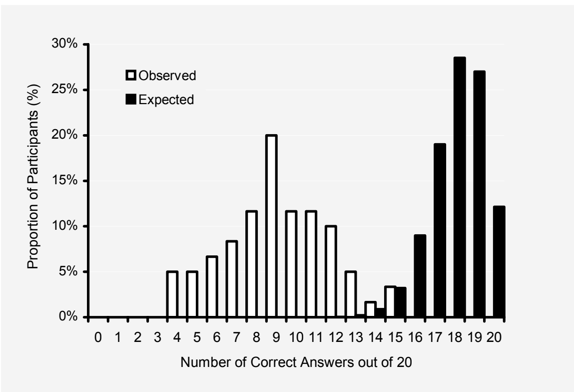

Figure 3: Participants' expected and observed scores on the 90% confidence calibration task.

"money" and "animal" scenarios reached standard levels of significance. A much more varied pattern exists for the cover stories (with p ranging from < .001 to .88), suggesting that some story-pairs may have been equivalent, but not all. Fortunately, however, none of the interaction effects were significant, with only the "animal" case being borderline (at $p = .08$). As a result, the effect of cover story can safely be disambiguated from the effect of frame, and the initial analysis suggesting an overall significant effect of frame is supported.

Framing and Memory. Overall susceptibility to framing was measured in terms of a "framing score" - the number of framing effects (preference reversals consistent with prospect theory) that a participant displayed. Higher framing scores therefore denote increased susceptibility to framing. The mean framing score obtained was 1.27 (*SD* = 1.19) out of 5. In total, 71.7% of participants reversed their preference at least once. The mean score on the backward Digit Span subtest from the WMS-III was 6.98 (*SD* = 2.20) and, on Retrieval Fluency, from the Woodcock-Johnson III, 78.15 (*SD* = 17.43).

Turning to the predicted correlation, participants who performed better on the two memory measures displayed no more framing effects than did participants with poorer memories. In fact, there was a weak tendency for higher backward digit span scores to be associated with less susceptibility to the framing effect ($\rho = –.31$, $p<.05$; see Table 4), a significant effect in the direction *opposite* to that predicted by our extension of DbS. Controlling for possible impacts of the intelligence measures – Ravens APM and Mill-Hill – and retrieval fluency did not noticeably affect this correlation, which remained at –.29. The correlation between framing score and retrieval fluency, was non-significant, weak and negative ($\rho = –.13$); the trend once again opposite in direction to our predictions. In this case, however, controlling for intelligence and digit span eliminated the trend, with ρ weakening to –.03.

Although this correlational analysis has the desirable characteristic of looking at the entire data set, and is designed to minimize the risk of false positives, it may be that – as discussed earlier – the memory effect exists for some types of question (e.g., money, for which Stewart et al. (2006) provided explicit distributions) but not others (e.g., community gains and losses, whose environmental distributions are unknown). With that in mind, we also conducted a finer grained analysis, which of course carries a much higher risk of false positives. To test the hypothesis of domain-specific memory effects on framing, independent samples *t*-tests were conducted, comparing the mean memory performance for people who showed prospect-theory consistent framing and those who showed no preference reversal. Across the 10 tests (5 domains x 2 memory measures) only two cases were significant at the two-tailed .05 level: people showing the framing effects for the community question had better retrieval fluency ($t(33) = 2.11$, $p = .04$), whereas working memory was *lower* among those who showed the effect for objects ($t(46) = –2.06$, $p = .04$). Obviously, if we make any reasonable correction for the inflation of false-positive errors caused by testing 10 hypotheses, both cases become non-significant. Overall, these results are unconvincing, with no evidence of any consistent relationship between individual differences in memory and framing susceptibility.

Overconfidence. We now consider the confidence data. As shown in Figure 3, perfectly calibrated individuals would be expected to average 18 hits out of 20 in our task, with the actual number following a binomial distribution with rate 0.9 and sample size 20. However, while the binomial model predicts that 95.7% of people should score in the 16-20 range, not one of our 60 participants did so. Not surprisingly, a single sample *t*-test of the hypothesis that the data arise from a distribution with mean 18 is highly significant, with $t(59) = –26.79$, $p<.001$. In short, participants were highly overconfident. Indeed, the average score of 8.8 out of 20 (*SD* = 2.66) implies that the ranges given were (on average) 44% intervals rather than 90% intervals.

Examining the data more closely, of the 1200 responses to items on the overconfidence test, participants rated a question as "easy" 252 times. Of these, 206 (81.8%) of the 90% ranges provided contained the actual answer, $CI_{98.3}$ = [75.9, 87.6]. Of the 389 times participants rated a question as being of "medium" difficulty, 169 (42%) ranges contained the actual answer $CI_{98.3}$ = [35.9, 47.9]. Finally, just 183 (32.7%) of the ranges participants gave for the 559 items they rated as "hard" contained the true answer $CI_{98.3}$ = [28.0, 37.5]. Since none of the three 98.3% confidence intervals[1] contained the value 90 (though the "easy" case is close), we conclude that participants were overconfident in each case (p<.05). Note, however, that the confidence interval for the "easy" questions in Figure 4 does not overlap the intervals calculated from the "medium" and "hard" items, indicating that the level of overconfidence in this case differs from the others. Visual inspection shows overconfidence increasing with difficulty, replicating the standard hard-easy effect for confidence calibration.

Memory and Overconfidence. To relate memory measures to overconfidence, a miscalibration level (the "overconfidence score") was calculated by taking the discrepancy between each participant's raw score, and the expected level of performance of 18/20. As shown in Table 4, the data display non-significant correlations in the predicted direction between backward digit span and the overconfidence score (ρ = –.19) and between retrieval fluency and the overconfidence score (ρ = –.14). However, Table 4 also shows that crystallized intelligence correlates significantly with the overconfidence score (ρ = –.31). With both intelligence measures and retrieval fluency controlled for, the relationship between backward digit span weakened to ρ = –.08, while in the case of retrieval fluency, controlling for intelligence and working memory measures caused the trend to reverse direction (ρ = .17), though it remained non-significant. Thus, overall, the evidence does not support our DbS-inspired prediction that memory would mediate overconfidence.

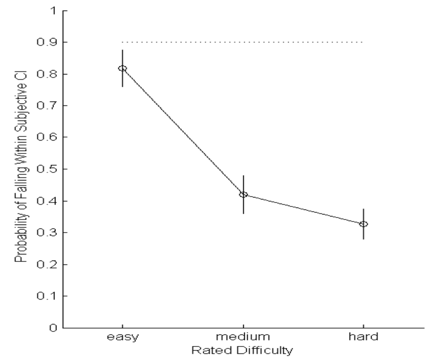

Figure 4: 98.3% confidence intervals for the 'easy,' 'medium' and 'hard' items on the overconfidence test.

Discussion

The results of this study offer no support for our extension of decision-by-sampling (DbS) theory: although the study reproduced other predicted effects (within- and between-subject framing, overconfidence, hard-easy effects, correlations between biases and intelligence), it uncovered no systematic relationships between memory and bias. In particular, it should be noted that a previously demonstrated (Koriat, Ma'ayan & Nussinson, 2006) relationship between overconfidence and retrieval was not replicated – due perhaps to the use of a different measure of overconfidence than the earlier research.

Some further caveats require mention. Firstly, the strength of the framing effect might be questioned. Only two of the five question pairs showed significant effects in their own right, perhaps resulting from the within-subjects design: traditional framing experiments use only between subjects designs (Tversky & Kahneman, 1981), though these designs have a more serious flaw, in that they cannot determine which participants are susceptible.

Unlike the memory measures, the intelligence measures did correlate with bias, in line with previous research (Stanovich and West, 1998). In particular, that participants with high crystallized intelligence are less overconfident is consistent with the results of Pallier et al. (2002) and with the hard-easy effect: participants with high crystallized intelligence will find more items on an overconfidence test 'easy' and thus produce more accurate ranges, leading to less overconfidence overall.

Finally, it should be noted that most of the correlations observed are weak, with only the Mill-Hill measure of crystallized intelligence having consistently significant correlations with the measures of bias susceptibility. This may reflect no more than a truncation in range resulting from a sample comprised entirely of undergraduate university students but still warrants caution when drawing conclusions.

General Discussion

Although this initial study does not support our extension of the DbS approach to include individual differences, it is important to recognize that what it rules out are only the strongest claims that the theory might encompass. In particular, although we did not find the predicted relationships between memory and decision-making *between people*, this is by no means the only interesting approach that DbS allows. The current study placed no controls on how participants made decisions; it sought to use individual differences to find the predicted effect. While this is appealing since it makes the decisions more "naturalistic" and is useful from an applied perspective (e.g., for debiasing), it necessarily loses some degree of experimental control. Since the effects do not emerge under "ordinary" circumstances, it makes sense to consider within-person effects, using artificial methods like response deadlining and imposing cognitive load to influence the decision sample.

The absence of strong effects also suggests other approaches: for instance, it may be that the measures of memory were not well chosen. Working memory capacity and fluency of retrieval were selected as they seemed, logically, to play the roles described for memory in DbS. However, they are not the only possibilities, so others might be worth considering. Along somewhat different

[1] In these analyses 98.3% confidence intervals were reported to ensure that the joint probability that all three values lay within the intervals remained at 95%.

lines, another test of DbS might examine the choice of reference class when making decisions – that is, the population from which samples are drawn. This could be tested by teaching people specific distributions of losses and gains before presenting a set of framing tasks. It could be determined whether this manipulation of the decision sample affects the decision made. Such a direct test is required given the absence of knowledge regarding the environmental distribution of losses and gains for most of the types of goods used in framing tasks – which would be required in order to predict, a priori, how people will react to changes in framing. In the absence of such knowledge it is, in many cases, impossible to determine whether it is the presence or absence of framing effects in a specific study that would support DbS.

In conclusion, the current failure to validate the theory rules out only our extension of the theory. It may be that DbS-related effects are strong enough to be observable across decisions made by a given person, but not so strong that they explain the variability in decisions between people.

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