**Why Do Delusion-Prone Individuals “Jump To Conclusions”? An Investigation Using A Non-Serial Data Gathering Paradigm**

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**Abstract**

That delusional and delusion-prone individuals gather less evidence before reaching a decision (“jumping to conclusions”) is arguably the most influential finding in the literature on cognitive theories of delusions. However, the cognitive basis of this data-gathering tendency remains unclear. Suggested theories include that delusion-prone individuals gather less data because they 1) misjudge the information value of evidence; 2) find data gathering more taxing than controls; and/or 3) make noisier decisions than controls. In the present study we developed a novel, incentivized, non-serial data-gathering task to tease apart these alternatives. Higher delusion-proneness was associated with gathering less information on this task, even when accounting for gender, risk aversion, and intelligence. Our findings suggest that misjudging the information value of evidence contributes substantially to the “jumping to conclusions” bias and that neither higher subjective costs nor noisy decision-making can fully account for it.

**Keywords**

Delusions; Delusion-Proneness; **Jumping to Conclusions; Data Gathering; Decision Making**

# Introduction

Delusions are errant beliefs, often with bizarre content, that feature in an array of psychiatric and neurological disorders and that may be present, in attenuated form, in the general population ([Linscott & Van Os, 2013](#_ENREF_28); [Peters, 2010](#_ENREF_34); [Van Os, Linscott, Myin-Germeys, Delespaul, & Krabbendam, 2009](#_ENREF_42)). Continuum models of psychotic symptoms ([Bentall, 2003](#_ENREF_5); [DeRosse & Karlsgodt, 2015](#_ENREF_10)) conceive of clinically significant delusions as occupying the extreme end of a spectrum of belief (e.g., [Freeman, Pugh, & Garety, 2008](#_ENREF_17); [Van Os & Reininghaus, 2016](#_ENREF_43)), and suggest that the non-clinical presentation of such symptoms might pose a risk factor for the development of clinical disorders (e.g., [Heriot-Maitland, Knight, & Peters, 2012](#_ENREF_23); [Kelleher et al., 2012](#_ENREF_26)).

As delusions can have devastating consequences in terms of suffering and impaired social and psychological functioning, a substantial body of research has investigated the cognitive anomalies associated with delusional ideation in both clinical and non-clinical populations. Perhaps the most influential finding in this literature is that delusional and delusion-prone individuals “jump to conclusions” ([Garety & Freeman, 2013](#_ENREF_20); [Huq, Garety, & Hemsley, 1988](#_ENREF_25)).

In a seminal study ([Huq et al., 1988](#_ENREF_25)), delusional participants observed an experimenter draw a series of beads from one of two hidden jars filled with beads of two colors in complementary ratios (85 pink/15 green in one jar, 85 green/15 pink in the other). The task for participants was to decide which jar the beads were being drawn from and to indicate at what point they were ready to make this decision. Relative to psychiatric and healthy control participants, delusional participants required fewer draws before deciding, with nearly half deciding on the basis of just a single bead. Based on this finding, and the results of many subsequent studies that have used this and similar paradigms with both clinical and non-clinical samples, a tendency to gather insufficient evidence when forming beliefs and making decisions is thought to play a key role in the formation of delusions ([for recent reviews and meta-analyses see Dudley, Taylor, Wickham, & Hutton, 2016](#_ENREF_13); [Garety & Freeman, 2013](#_ENREF_20); [McLean, Mattiske, & Balzan, in press](#_ENREF_30); [Ross, McKay, Coltheart, & Langdon, 2015](#_ENREF_37); [So, Sie, Wong, Chan, & Garety, 2016](#_ENREF_38)).

To date, however, the cognitive basis of this data-gathering tendency remains uncertain. One possibility is that delusion-prone individuals mis-value or mis-integrate relevant information when updating beliefs, perhaps overweighting direct sensory evidence and underweighting prior beliefs ([Adams, Stephan, Brown, Frith, & Friston, 2013](#_ENREF_1); [McKay, 2012](#_ENREF_29); [Menon, Pomarol-Clotet, McKenna, & McCarthy, 2006](#_ENREF_31); [Speechley, Whitman, & Woodward, 2010](#_ENREF_39)). Another possibility is that delusion-prone participants find data gathering more taxing than controls do. In the context of the beads task, they may become more easily fatigued as the task progresses and may request fewer draws simply in order to escape the study ([cf. Dudley & Over, 2003](#_ENREF_12); [White & Mansell, 2009](#_ENREF_44)).

A third explanation was proposed by [Moutoussis, Bentall, El-Deredy, and Dayan (2011)](#_ENREF_32), who analysed beads task data previously obtained by [Corcoran et al. (2008)](#_ENREF_8). They fit two different statistical models to these data, concluding that the data were more consistent with delusional individuals making *noisier* decisions than control participants, than with delusional individuals experiencing higher subjective costs of collecting evidence. (Moutoussis et al.’s study did not allow an “explicit comparison with … systematic deviations from the Bayesian norm” ([2011, p. 19](#_ENREF_32)), so did not address the evidence-overweighting account.) In a serial task such as the classic beads task, such noisy decision-making can manifest as “jumping to conclusions”. To see this, consider that after each bead is drawn, a participant must choose whether or not to sample an additional bead. At each point, if the optimal decision is to sample further, noisier decision-makers will be more likely to cease sampling (compared to less noisy decision-makers); and if the optimal decision is to cease sampling, noisier decision-makers will be more likely to sample further. Because a decision to cease sampling ends the task, if the optimal stopping point is several beads into the sequence, noisy decision-makers will tend to cease sampling in advance of this point and will not get the opportunity to err on the side of sampling too much.

We can thus distinguish three different explanations for the classic “jumping to conclusions” effect: 1) delusion-prone individuals mis-value relevant information when forming beliefs and making decisions; 2) the subjective cost of data gathering is greater for delusion-prone individuals than for non-delusion-prone individuals; and 3) delusion-prone individuals make noisier decisions than non-delusion-prone individuals. In the present study we developed a novel version of the beads task in an attempt to tease apart these three alternatives. Whereas in the standard task participants see an initial piece of information (a single coloured bead), then choose either to sample further or to make their decision about the information source, our task is non-serial*.* Participants in our task make a single decision *up front* about how many pieces of information they want to sample in total, and the requested information is then displayed simultaneously on screen, rather than serially. No additional sampling is possible.

This paradigm eliminates the additional time and effort that serial decisions require. As all requested information is displayed simultaneously, participants cannot finish the task any earlier by choosing to request less information. If the tendency of delusion-prone participants to gather fewer data on the beads task is due to motivational factors, we would therefore expect this effect to disappear on our non-serial variant of the task. However, if the standard “jumping to conclusions” effect is attributable to delusion-prone individuals overweighting the information value of evidence, then the effect should persist on our task, with more delusion-prone participants requiring less evidence to base their decisions upon than less delusion-prone participants. Finally, if “jumping to conclusions” on the serial task is attributable to noisy decision-making, delusion-prone individuals should display a larger variance in their decisions, but request a similar amount of evidence on average.

Aside from attempting to disambiguate the three theoretical alternatives described above, we took steps to control for the influence of a range of other factors. First, some authors have suggested that participants in serial beads task paradigms might erroneously believe that the information source can switch from one information sample to the next (e.g., thinking that some beads in a sequence have come from the first jar and others from the second; [Balzan, Delfabbro, & Galletly, 2012](#_ENREF_3); [Balzan, Delfabbro, Galletly, & Woodward, 2012](#_ENREF_4)). Our non-serial task minimizes the possibility that participants can miscomprehend the task in this way, as there is just a single information sampling decision for each scenario. Our use of detailed written instructions, comprehension questions, monetary incentives, and the more intuitive lakes-and-fish adaptation of the task ([Speechley et al., 2010](#_ENREF_39); [Whitman & Woodward, 2011](#_ENREF_45)) also help to minimize miscomprehension and maximize task engagement.

Related to miscomprehension, limitations or deficits in working memory may influence sampling decisions by impairing participants’ ability to maintain and manipulate relevant task information, such as the ratios of the beads in the jars or the sequence of beads presented in serial paradigms ([Dudley, John, Young, & Over, 1997](#_ENREF_11)). Indeed, associations between “jumping to conclusions” and poor working memory have been documented for participants at risk of developing a psychotic disorder ([Broome et al., 2007](#_ENREF_7)) and for delusional patients (e.g., [Freeman et al., 2014](#_ENREF_18); [Garety et al., 2013](#_ENREF_21)). To reduce memory load in the present study we depicted relevant information onscreen screen (e.g., visually and numerically presenting the ratios of black to white fish in each lake). Finally, given that some studies have found that the association between jumping to conclusions and delusions disappears when controlling for intelligence ([see Lincoln, Ziegler, Mehl, & Rief, 2010](#_ENREF_27)), intelligence was also measured and accounted for in our analyses – as was risk-aversion.

# Methods

## Participants

Participants were 112 students (59 females; mean age = 19.94, *SD* = 2.92) from Royal Holloway, University of London (RHUL). Participants were recruited using the Online Recruitment System for Economic Experiments ([ORSEE; Greiner, 2004](#_ENREF_22)). The study protocol was approved by the RHUL Psychology Department Ethics Committee, and the study was carried out in accordance with the provisions of the World Medical Association Declaration of Helsinki.

## Materials

### Decision task

The task comprised five trials. On each trial, participants were shown a fisherman who had caught fish from one of two lakes containing black and white fish in complementary ratios (25:75 or 75:25). Participants were asked to indicate how many fish (between one and ten fish, inclusive) they wanted to see from the fisherman’s catch before deciding whether all the fish were from Lake A or B. It was emphasized that on each fishing trip (corresponding to a trial) the fisherman visited one of the lakes only and was equally likely to visit either lake. Next, participants were shown their requested number of fish all at once and were required to decide which of the two lakes the fisherman had been fishing from. To accomplish this, one of the two lakes was selected randomly as the “correct” lake and an appropriately sized sample of fish was drawn randomly from that lake, in accordance with the corresponding ratios of black and white fish. Choosing the correct lake was rewarded with experimental points, but a small cost was incurred for each fish requested (this cost was deducted from the potential reward, such that costs were only realised for participants who chose the correct lake). These incentives varied from trial to trial, leading to different optimal numbers of fish to request across trials (see Table 1; calculations are presented in the Supplemental Online Material).[[1]](#footnote-2) To reduce cognitive load, our visual stimuli (based on those used by [Speechley et al. (2010)](#_ENREF_39)) included explicit information about the ratios in the lakes and the incentive structure.

### Delusion-proneness

We used the 21-item Peters et al. Delusions Inventory ([PDI; Peters, Joseph, Day, & Garety, 2004](#_ENREF_35)) to measure proneness to delusions. Participants answered a series of yes/no items (e.g., “Do you ever feel as if you are being persecuted in some way?”). For each item endorsed, participants rated their levels of distress, preoccupation and conviction for that item on separate 5-point scales. PDI scores (comprising the sum of the endorsed items plus the summed scores for each dimension) could range from 0-336.

### Intelligence

We used the short (12-item) version of Raven’s Advanced Progressive Matrices ([APM; Arthur & Day, 1994](#_ENREF_2)) to measure intelligence. We set a time limit of 15 minutes for these twelve items. APM scores represent the number of correct answers, with higher scores indicating higher intelligence.

### Risk aversion

We used Holt and Laury’s (2002) measure of risk aversion. This measure involves ten decisions between two gambles, for example a decision between Option A “A 7/10 chance of winning £2.00, a 3/10 chance of winning £1.60” and Option B “A 7/10 chance of winning £3.85, a 3/10 chance of winning £0.10” ([Holt & Laury, 2002, based on p. 1645](#_ENREF_24)). With each successive decision, the probability of the high payoff outcome in each option increases by 10%, such that the expected value of the “risky” Option B increases. Risk aversion was defined as the total number of times Option A was chosen, with higher scores indicating higher risk aversion.

## Procedure

Participants were tested in groups of 20 to 26 people. All sessions were conducted using z-Tree software ([Fischbacher, 2007](#_ENREF_16)) in the experimental economics laboratory (EconLab) at RHUL. Each session began with an incentivised, serial version of the task, reported elsewhere ([Van der Leer, Hartig, Goldmanis, & McKay, 2015](#_ENREF_41)). Before beginning the non-serial data-gathering task, participants read detailed instructions and had to correctly answer a series of comprehension questions. Across testing sessions, the five trials of the task were presented in an incomplete counterbalanced order, accomplished through Latin square counterbalancing, using maximally different orders across sessions. The first trial had a time limit of 60 seconds to acquaint participants with the task, whereas the other trials had time limits of 20 seconds each to discourage formal calculations (e.g., using mobile phones). Next, participants completed the risk aversion measure, the PDI, the APM, and demographic questions. At the end of the session participants were paid £0.05 for each experimental point earned.

# Results

## Descriptives

The sample’s PDI scores ranged from 10-253 (mean=75.06, median=68.5, SD=40.61), APM scores ranged from 1-12 (mean=6.62, median=7, SD=2.94), and risk aversion scores ranged from 0-9 (mean=5.41, median=6, SD=1.73). In Table 1 we report the incentive structure (potential reward and cost per fish), optimal number of fish to request, and the mean number of fish actually requested on each trial, both for the full sample and for the two outer quartiles reflecting low-delusion-prone and high-delusion-prone participants. In Table 2 we report zero-order correlations between our variables of interest.

- Insert Tables 1 and 2 about here -

## Task validation

To investigate the convergent validity of our non-serial data-gathering task, we correlated the average number of fish requested across trials in the task with the average number of fish requested across five trials of the serial version of the task. The correlation was highly significant and positive, *r* = .65, *p* < .001.

## Task performance

To investigate the relationship between data gathering and delusional ideation we conducted a random effects regression with number of fish requested as the criterion variable and optimal number of fish, delusion-proneness (PDI), gender, intelligence (APM), and risk aversion as predictor variables. This analysis confirmed that participants higher in delusional ideation requested fewer fish in order to decide on a lake (see Table 3; Model specifications 2-5). For example, the person with the highest PDI score (253) was estimated to choose between two and three fewer fish (out of a possible ten) than the person with the lowest PDI score (10).

In contrast, participants higher in intelligence (APM) requested *more* fish (Model specifications 4 and 5). This association is consistent with some previous research using the beads task (e.g., see [Van Dael et al., 2006)](#_ENREF_40).

We also conducted a standard OLS-regression using averaged data: that is, we regressed the number of fish requested (averaged across the five trials) on PDI scores, and checked whether effects remained when control variables (gender, intelligence, risk aversion) were accounted for. The results were identical: PDI negatively predicted the number of requested fish when entered alone or in combination with any subset of control variables (all models with PDI were significant, PDI itself was always a significant individual predictor, and the addition of PDI to any combination of predictor variables significantly improved the model fit).

We thus find the classic relationship between data gathering and delusional ideation in a decision paradigm free of motivation and noise confounds: higher delusion-proneness was associated with gathering less information on the task, even when accounting for gender, intelligence and risk aversion.

Furthermore, the results confirmed that our participants took the incentives into account and adjusted their decisions accordingly (Table 3; in all five model specifications the optimal number of fish was a positive predictor of the number of fish actually requested). However, adjustments were clearly much weaker than optimal.

- Insert Table 3 about here -

Our data supply only weak evidence that delusion-prone individuals make noisier decisions. The variance of the high-delusion-prone group’s data-gathering decisions was numerically greater for each trial than the variance of the low-delusion-prone group’s decisions (Table 1), but the differences were all non-significant (all *p*s>.05 in Levene’s test for equality of variances). Likewise, comparing individual choices across trials A and D (which should have been the same: trial A had double the potential reward and double the cost-per-fish of trial D, so the optimal number of fish to request was identical for both trials), the average absolute difference between the number of fish requested on these two trials was numerically greater for the high-delusion-prone subset (Mean absolute difference = .75, SD = 1.32) than for the low-delusion-prone subset (Mean absolute difference = .36, SD = 0.73), but this difference was not significant (*t*[54]=1.37, *p*=.175) and the correlation between the difference and PDI was also very weak (Spearman *ρ* = .049, *p*=0.61).

# Discussion

That delusional and delusion-prone individuals “jump to conclusions” is one of the most prominent claims in the literature on delusions. In the standard paradigm (the classic “beads task”) participants can sample a series of information, one piece at a time. In naturalistic settings, such serial data gathering can be costly and dangerous, consuming both time and cognitive resources ([Furl & Averbeck, 2011](#_ENREF_19)). Humans should therefore be predisposed to weigh such costs against the costs of incorrect decisions. Even when data gathering is associated with explicit, objective costs ([Furl & Averbeck, 2011](#_ENREF_19); [Van der Leer et al., 2015](#_ENREF_41)), however, the *subjective* cost of gathering data may vary between individuals. This raises the possibility that delusion-prone individuals reach earlier conclusions on the standard, serial beads task because they find data gathering more onerous than controls do. If this were the case, there would be nothing *irrational* about “jumping to conclusions”: both high-delusion-prone and low-delusion-prone individuals could be responding rationally to their own idiosyncratic incentives.

In an important study, [Moutoussis et al. (2011)](#_ENREF_32) analysed serial beads task data using two models, one of which was based on calculating the potential costs of decision-making. These authors argued that their analysis did not support the hypothesis that the subjective cost of collecting evidence is greater for delusional individuals. In the present study we examined this issue at the level of methodology rather than analysis, by developing a non-serial version of the beads task in which the gathering of extra evidence was not more time-consuming or effortful. The fact that delusion-prone individuals gathered less data on this novel task cannot be explained in terms of the subjective costs of data gathering, because the process of gathering maximal information was no more involved than the process of gathering minimal information.

However, according to the Moutoussis et al. conceptual model, the subjective cost explanation of jumping to conclusions can actually refer to two inter-related costs: on the one hand the subjective cost of data gathering, and on the other hand the subjective cost of being wrong (cost-of-sampling and cost-of-wrong-decision, respectively, in Moutoussis et al’s terminology). Up to this point we have considered only the first of these, but what about the second? Compared to controls, delusion-prone individuals might find it less intrinsically aversive to be wrong about the source of the fish ([perhaps they care less about impressing the experimenter for instance; see Dawes, 1996](#_ENREF_9)). As with the subjective cost of data gathering, this could manifest in these individuals viewing fewer data than non-delusion-prone individuals, but here this could be the case both on serial tasks *and* on our non-serial task. While we acknowledge this possibility, we highlight that our study incorporated explicit costs-of-sampling and explicit costs-of-wrong-decisions, such that on each trial there was an ‘optimal’ number of fish to request, i.e., a number of fish that would maximize expected outcome. Under such incentives, we suggest that it is natural to construe “good performance” as performance that maximizes expected outcome, and thus that participants with an intrinsic motivation to perform well would focus on this rather than on being correct about which lake the fish were coming from. We therefore doubt that the relationship we observed between delusional ideation and data gathering could be driven by less delusion-prone participants caring unduly about getting the source of the lake right (to the extent that they actually lost money).

We thus believe our results are consistent with those of [Moutoussis et al. (2011)](#_ENREF_32) in undermining the “subjective cost” explanation of “jumping to conclusions”. However, whereas Moutoussis et al. suggested instead that the jumping to conclusions effect arises because delusional individuals make *noisier* decisions than control participants, the data-gathering disparity we found cannot be an artefact of noisy decision-making because our non-serial paradigm eliminates the asymmetry in opportunities to err on the side of sampling too much versus too little.

Although our findings do not provide convincing evidence that delusion-prone individuals do in fact make noisier decisions, our measures of noisy decision-making may have been too weak to be really meaningful – a fuller test of the noise model may require multiple observations of each unique decision. We also note that the Moutoussis et al. (2011) analysis was carried out on a large transdiagnostic sample of patients. Given that executive impairment has been often reported for patients with psychosis, and given that impaired executive functioning was found to contribute to paranoia in other analyses of the Moutoussis sample ([e.g., Bentall et al., 2009](#_ENREF_6)) it is reasonable to expect the noise parameter to be more important in clinical groups.

In any case, while noisy decision-making may contribute to “jumping to conclusions” in standard, serial decision paradigms, our data suggest that noise cannot wholly account for this effect. Instead, we suggest that delusion-prone individuals mis-value relevant information when forming beliefs and making decisions; in particular, overweighting the information value of direct sensory evidence and underweighting background information ([Adams et al., 2013](#_ENREF_1); [McKay, 2012](#_ENREF_29); [Menon et al., 2006](#_ENREF_31); [Speechley et al., 2010](#_ENREF_39)). As a result, they require fewer pieces of evidence – whether presented serially or otherwise – before reaching decisions.

As the present study utilised a non-clinical sample, we recommend that future studies take advantage of our non-serial variant of the beads task to further explore the data gathering behaviour of delusional patients. According to a recent meta-analysis (Ross et al., 2015) the size of the relationship between data gathering and delusional ideation was very similar in general population and current delusions subgroups. Although we believe this justifies the dimensional approach we have taken here (exploiting variation in the healthy population so as to provide insight into the aetiology of clinical delusions), using the present paradigm to confirm this relationship in clinical samples will further illuminate the underpinnings of these perplexing and distressing symptoms.

# Author Contributions

All authors contributed to the study design. Testing and data collection were performed by L.V.D.L. and B.H. L.V.D.L., B.H. and R.M. performed the data analysis and interpretation. All authors wrote the paper and approved the final version of the paper for submission.

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# Tables

Table 1: The incentive structure, optimal number of fish to request, and mean (SD) number of fish actually requested for each trial. Rewards and costs are in experimental points (1 point = £0.05).

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  |  | Trial A | Trial B | Trial C | Trial D | Trial E |
| Potential reward | | 100 | 50 | 200 | 50 | 50 |
| Cost per fish | | 2 | 3 | 2 | 1 | 2 |
| Optimal number of fish to request | | *5* | *1* | *9* | *5* | *3* |
| Mean (SD) number of fish requested | Full sample (n=112) | 5.17  (2.01) | 4.25  (1.75) | 5.48  (2.54) | 5.10  (2.25) | 4.52  (1.97) |
| Low-delusion-prone (n=28) | 5.25  (1.84) | 4.14  (1.60) | 5.75  (2.52) | 5.11  (1.75) | 4.71  (1.72) |
| High-delusion-prone (n=28) | 4.86  (2.44) | 3.89  (1.93) | 4.79  (2.82) | 4.68  (2.46) | 4.00  (2.18) |

Table 2: Zero-order correlations (Spearman’s rho). PDI: Peters et al. Delusions Inventory (delusion-proneness); APM: Advanced Progressive Matrices (intelligence).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Av. no. fish | PDI | Gender | APM | Risk aversion |
| Average number of fish requested | - | -0.20\* | -0.18 | 0.35\*\* | 0.14 |
| PDI |  | - | 0.19\* | -0.02 | -0.18 |
| Gender |  |  | - | -0.16 | 0.09 |
| APM |  |  |  | - | 0.08 |
| Risk aversion |  |  |  |  | - |

*Note*: \* *p*<.05, \*\* *p*<.01

Table 3: B-values for each of the predictors in five model specifications of a random effects regression with number of fish requested as the dependent variable. PDI: Peters et al. Delusions Inventory (delusion-proneness); APM: Advanced Progressive Matrices (intelligence).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
| Optimal number of fish | 0.162\*\* (0.019) | 0.162\*\* (0.019) | 0.162\*\* (0.019) | 0.162\*\* (0.019) | 0.162\*\* (0.019) |
| PDI |  | -0.011\* (0.004) | -0.010\* (0.004) | -0.009\* (0.004) | -0.008\* (0.004) |
| Gender |  |  | -0.550 (0.339) |  | -0.416 (0.330) |
| APM |  |  |  | 0.201\*\* (0.0559 | 0.190\*\* (0.055) |
| Risk aversion |  |  |  | 0.075 (0.094) | 0.091 (0.095) |
| Intercept | 4.159\*\* (0.194) | 4.947\*\* (0.367) | 5.163\*\* (0.388) | 3.124\*\* (0.751) | 3.264\*\* (0.757) |
| Observations  (groups of independent observations) | 560  (112) | 560  (112) | 560  (112) | 560  (112) | 560  (112) |
| R² (within, between, overall) | – ­­– 0.040 | 0.137 0.054 0.078 | 0.137 0.077 0.094 | 0.137 0.166 0.157 | 0.137 0.178 0.166 |

*Note*: Standard errors are in parentheses; \* *p*<.05, \*\* *p*<.01

# Supplemental Material: Why Do Delusion-Prone Individuals “Jump To Conclusions”?

# Calculation of the optimal sample size in the non-serial data gathering paradigm

Let the lakes be Lake White (with more white than black fish) and Lake Black (with more black than white fish). Let the probability of catching a white fish in Lake White and the probability of catching a black fish in Lake Black both equal (so that ):

Let the observer have a uniform prior over lakes:

Now, suppose we have sampled fish and found that of them are white (so that are black). What is our best guess of the lake the fisherman was fishing from? Given that the prior probabilities of both lakes are the same, it is clear that we should guess "Lake White" if we have sampled more white than black fish () and "Lake Black" if we have sampled more black than white fish (). If we have observed the sample gives us no information, so we can make either guess, and it will be correct with probability 1/2.

Given this decision rule, what is our probability of making a correct guess based on a sample of fish? Clearly, for an odd this is simply the probability that we get more fish of the "correct" than of the “incorrect” color (where the “correct” color is white if the true lake is Lake White and black if the true lake is Lake Black). For an even , we need to add to this one half of the probability that we draw equal numbers of fish of both colors. To calculate these quantities, we simply note that we can get of the fish in the correct color in ways, and each of these occurs with probability , so that the total probability of getting of the fish in the “correct” color is:

Thus the probability of a correct decision for any odd , i.e., for any , where is a natural number, is:

The probability of a correct decision for any even n, i.e., for any , where is a natural number, is:

Suppose that the cost is c per fish, while the reward for a correct guess is R. Then the total expected payoff after sampling n fish is:

The optimal sample size maximizes this expression:

An even is never optimal: Intuitively, increasing the sample size by one from any odd number can never be optimal, since adding the fish can never meaningfully change the optimal decision. Mathematically, we can show that for any :

so that:

.

The problem thus reduces to:

1. Strictly speaking these decisions are only “optimal” with respect to the maximization of expected outcome (i.e., from a risk neutral perspective). [↑](#footnote-ref-2)