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Supplementary Materials for

Wise or mad crowds? The cognitive mechanisms underlying information cascades

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Supplementary Information

Supplementary Results

Using the Two-stage Dynamic Signal Detection (2DSD) model to model the personal phase: To model the personal choice phase, we used the two-stage dynamic signal detection (2DSD) model. The 2DSD model is an evidence accumulation model that can account for choice and response time (RT) in the personal choice and the associated confidence judgement. In so doing, it can identify cognitive mechanisms potentially governing the interrelationships of these behavioral measures (17). Like other evidence accumulation models, it assumes that individuals gather evidence over time until the amount of evidence surpasses a threshold. The two key assumptions of the 2DSD model are that evidence accumulation continues after the decision is made and that reported confidence depends on the evidence accumulated at the time of the confidence judgement. Thereby, the evidence state is mapped into confidence judgements using response criteria that serve as thresholds indicating the next higher confidence judgements (e.g., from 50 to 60, or 60 to 70). See Pleskac & Busemeyer (2010) for a detailed description of the 2DSD model.

We fitted the model in the hierarchical Bayesian framework, implemented with RStan in R (61, 62), with five parallel chains with 10,000 iterations each and a thinning factor of 10. The first half of the iterations were discarded as burn-in. Descriptions of the main parameters are given in Supplementary Table **??**. For the Wiener diffusion process, we included boundary separation α, predecisional drift rate δ_{pre}, relative start point z, and nondecision time NDT, which was calculated relative to the fastest response. Some trials were expected to be more difficult than others, because the number of sharks could be closer to (i.e., 4 and 6) or further away from (i.e., 3 and 7) the threshold number of sharks (5). We accounted for variations in difficulty by varying the predecisional drift rate δ_{pre}, depending on trial difficulty:

$$\delta_{pre} = \begin{cases} \delta_{difficult}, & \text{if } 4 \text{ or } 6 \text{ sharks present} \\ \delta_{difficult} + \Delta_{easy}, & \text{if } 3 \text{ or } 7 \text{ sharks present} \end{cases} \tag{9}$$

with Δ_{easy} describing the additional effect of easy trials on the drift rate. For the postchoice process, we fitted confidence criteria and the postdecisional drift rate (δ_{post}). The postdecisional drift rate is influenced by the predecisional drift rate, with the parameter w controlling its strength, and δ_{choice} describing the influence of the choice on the subsequent drift:

$$\delta_{post} = \begin{cases} w \times \delta_{pre} + \delta_{choice}, & \text{if correct} \\ w \times \delta_{pre} - \delta_{choice}, & \text{if incorrect} \end{cases} \tag{10}$$

The evidence distribution at the time point when confidence is reported L_{conf} is a combination of the evidence accumulated at the time point of choice and the evidence accumulated between choice and confidence judgement. It is normally distributed with a mean of

$$E[L_{conf}] = \begin{cases} \alpha + \delta_{post} \times IJT, & \text{if correct} \\ 0 + \delta_{post} \times IJT, & \text{if incorrect} \end{cases} \tag{11}$$

and a variance of

$$var[L_{conf}] = \sigma^2 IJT \tag{12}$$

with IJT being the interjudgement time (i.e., the time between choice and confidence reporting).

Each decision maker has confidence criteria c_j to map the evidence state L_c into six possible confidence judgements $conf_j$ with $j = 0, 1, 2, ...5$, corresponding to the confidence levels 50 to 100. The probability of reporting $conf_j$ is given by the normal cumulative distribution $\sim \mathrm{N}\left(E[L_c], var[L_c]\right)$ with:

$$P(c_j < L_c < c_{j+1}) \tag{13}$$

where c_0 is equal to $-\infty$ and c_6 to ∞. The five remaining confidence criteria are fitted by the model. We assume the locations of the confidence criteria for correct and incorrect choices to be symmetrical. Hence, we set the locations relative to the choice thresholds with $alpha + c_j$ and $0 - c_j$ for correct and incorrect choices, respectively. For the fitting process, we excluded all choices with RTs below 0.1 sec. To compare the predictions of the model with the empirical data, we generated choices, RTs, and confidence judgements using the participant's mean posterior parameter estimate. The confidence judgements were generated by sampling from the evidence distribution at the time point of the judgement and mapping this evidence state to a confidence judgement. We thus obtained confidence judgements given the individual's choice, RT, and interjudgement time. To account for stochasticity generated by the sampling process, we sampled 100 confidence judgements, choices, and RTs per individual and trial.

2DSD model results: Participants drifted towards the correct choice threshold ($\delta_{difficult} = 0.37$, CI = [0.33, 0.41]). Trials with three or seven sharks were easier than trials with four or six sharks, as indicated by a stronger drift towards the correct option in the former ($\Delta_{easy} = 0.05$, CI = [+0.00, 0.10]). Varying drift rates depending on difficulty were not included in the social DDM analysis, as the effect was comparatively small. After making a choice, participants continued accumulating evidence and, on average, kept gathering correct evidence ($w = 0.72$, CI = [0.62, 0.83]). Hence, participants who made an incorrect decision gathered more evidence over time contradicting their initial choice (resulting in lower confidence), whereas the evidence of those who made a correct choice was strengthened (resulting in higher confidences). This process explains the increasing difference in confidence ratings between correct and incorrect choices as interjudgement time increases (Supplementary Fig. **??**A). Additionally, there was a choice effect on the postdecision drift, whereby participants accumulated evidence in favour of their already chosen option ($\delta_{choice} = 1.64$, CI = [1.47, 1.80]). As a result, longer interjudgement times are predicted to lead to higher confidence judgements (Supplementary Fig. **??**B). Figure **??**C shows that the 2DSD recreates the well-established relationship between confidence and accuracy, which is partly determined by the postdecisional processing evident in Figures **??**A and B. In both the 2DSD and the social DDM analysis, we thus found that confidence is linked to the evidence state and that participants drifted in the direction of their chosen option (i.e., reinforced their 'belief' in their original choice). Figure **??**D shows RT distributions for the personal choice. Overall, the empirical data (solid lines) correspond closely with the predictions of the 2DSD model (dashed lines), indicating that the personal phase can be described by a drift diffusion process. One distribution characteristic the model cannot recover is the higher average RTs for incorrect choices. This is a well-known property of the drift–diffusion model, and can be addressed by adding trial-by-trial variability to the drift rates (19). For simplicity, we have not included trial-by-trial variability.

Supplementary Figures

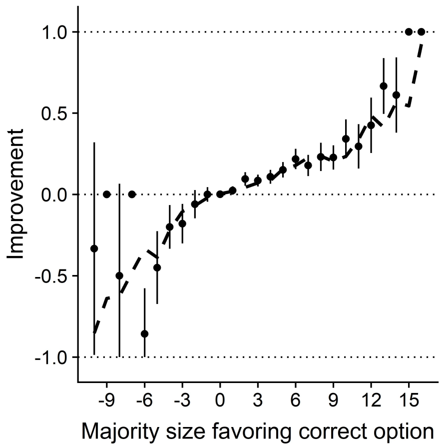

Figure S1: **Improvement during the social phase depended on the quality of social information.** Participants' choices were increasingly likely to improve/worsen as the size of the majority for the correct/incorrect option increased. Dots represent the mean; error bars represent twice the standard error. The dashed line shows the prediction of the social DDM.

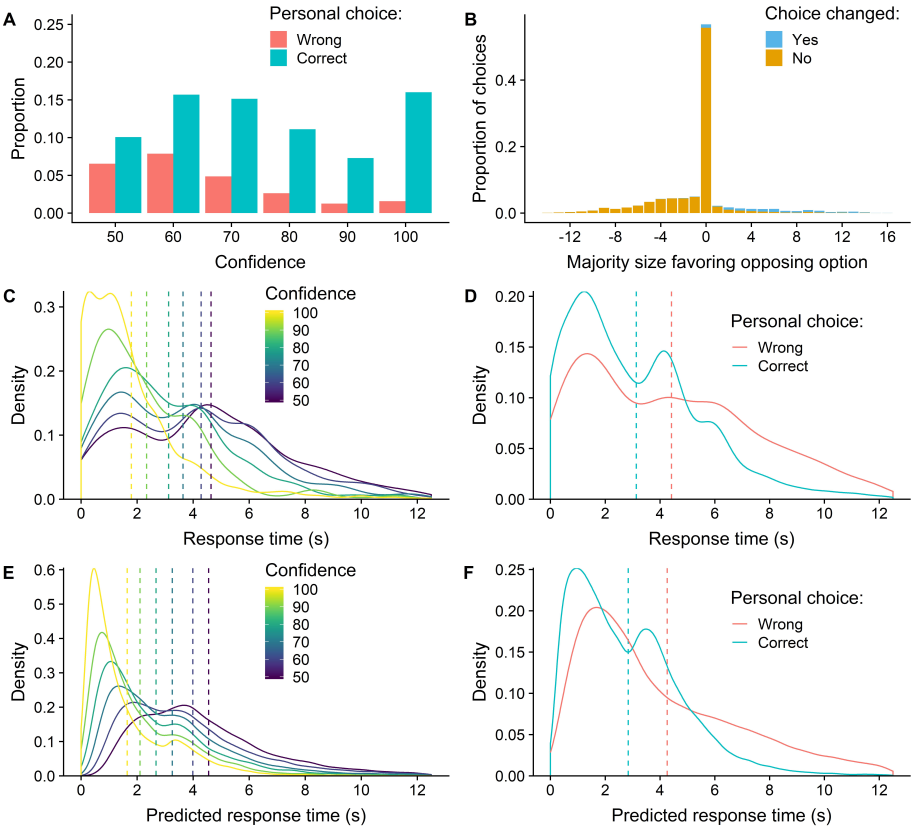

Figure S2: **Distributions of key behavioural measures.** **(A)** The proportion of reported confidence scores for correct and incorrect choices. The higher the confidence score, the larger the proportion of correct choices, resulting in a positive confidence–accuracy relationship (see also Supplementary Fig. **??**C). **(B)** The proportion of choices made in the presence of different majority sizes. In the social phase, most choices ($\approx 60\%$) were made in the absence of a majority, and participants who experienced a majority were more likely to observe a confirming majority (i.e., negative values) than an opposing majority. Participants facing an opposing majority were more likely to change their choice the larger the size of this opposing majority. **(C)** Observed RT distributions during the social phase as a function of reported confidence. Participants reporting the highest level of confidence overwhelmingly responded within 4 seconds, whereas the distribution of participants reporting the lowest confidence level peaked after 4 seconds. **(D)** Observed RT distributions during the social phase for correct and incorrect choices. Given that unconfident participants are more likely to be wrong and waited longer, it follows that individuals who were wrong, on average, wait longer to respond. **(E, F)** RT distributions as predicted by the social DDM. The model recovers not only the relationship of RT with confidence and accuracy, but also the shape of the RT distributions. The RT distributions are multimodal because social information was first updated after 3 seconds and then every 2 seconds. Majority sizes often increased with each updating event resulting in an increasing likelihood of a response by a increase in the drift rate. **(C–F)** Dashed vertical lines represent the mean RTs.

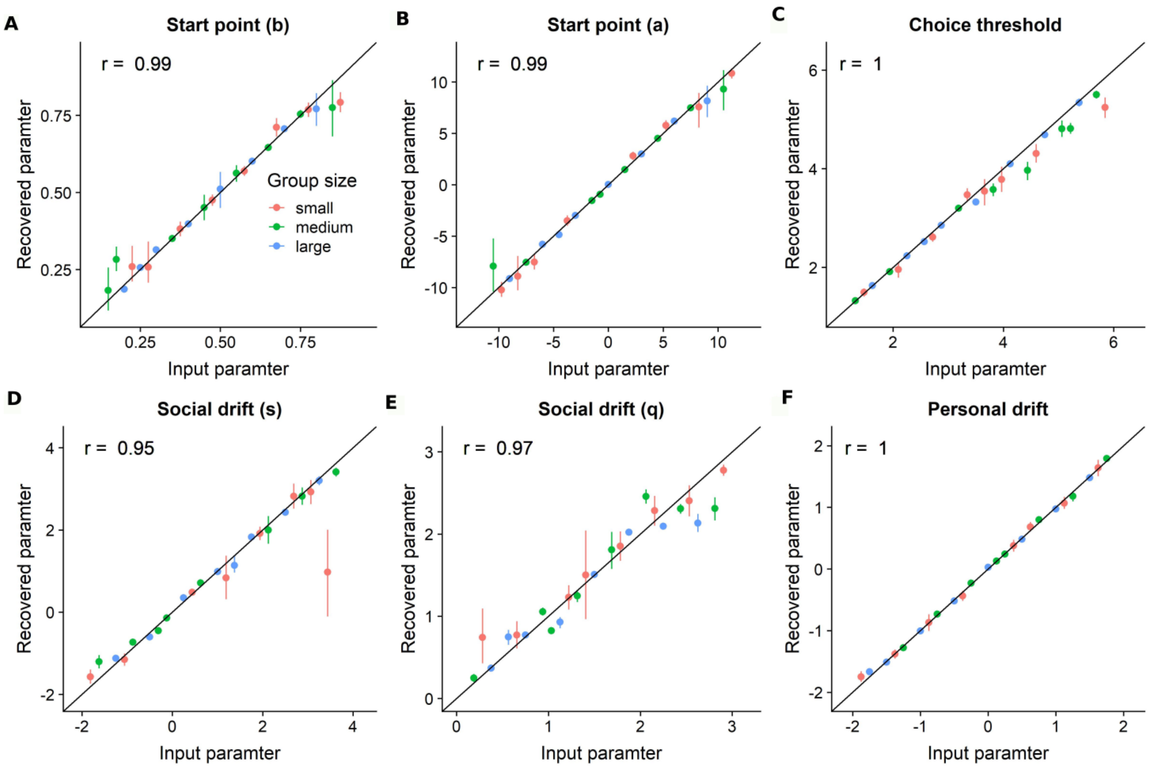

Figure S3: **Model recovery.** The x-axis shows the actual (input) parameters; the y-axis shows the recovered parameters. The figure shows the results of a parameter recovery analysis conducted to ensure that the parameters of the social DDM are interpretable and capture distinct cognitive mechanisms. We repeatedly generated data with random input parameters and recovered them with the same hierarchical social DDM used to analyse the empirical data. The input parameters were sampled with a quasirandom number generator (using the sobol sequence), ensuring an even distribution across a large multidimensional parameter space. Using these input parameters, we generated social choices by computing probability density functions while taking into account the personal choice, reported confidence, and the social information observed by the participant at a given trial. The generated data thus have the same hierarchical structure as the empirical data, with 141 participants and varying group size. Again, we report the mean of the posterior distributions and the 95% CI of the higher order group-level estimate for each group size. To measure the relationship of input and recovered parameters, we calculated Spearman's correlation coefficient r for all parameters (except nondecision time, which is relative to a participant's fastest response and thus meaningless on a group level). For all parameters, there was a strong positive correlation between the generated and the recovered parameters. The estimates provided by the social DDM thus describe separate identifiable features and are interpretable in their magnitude.

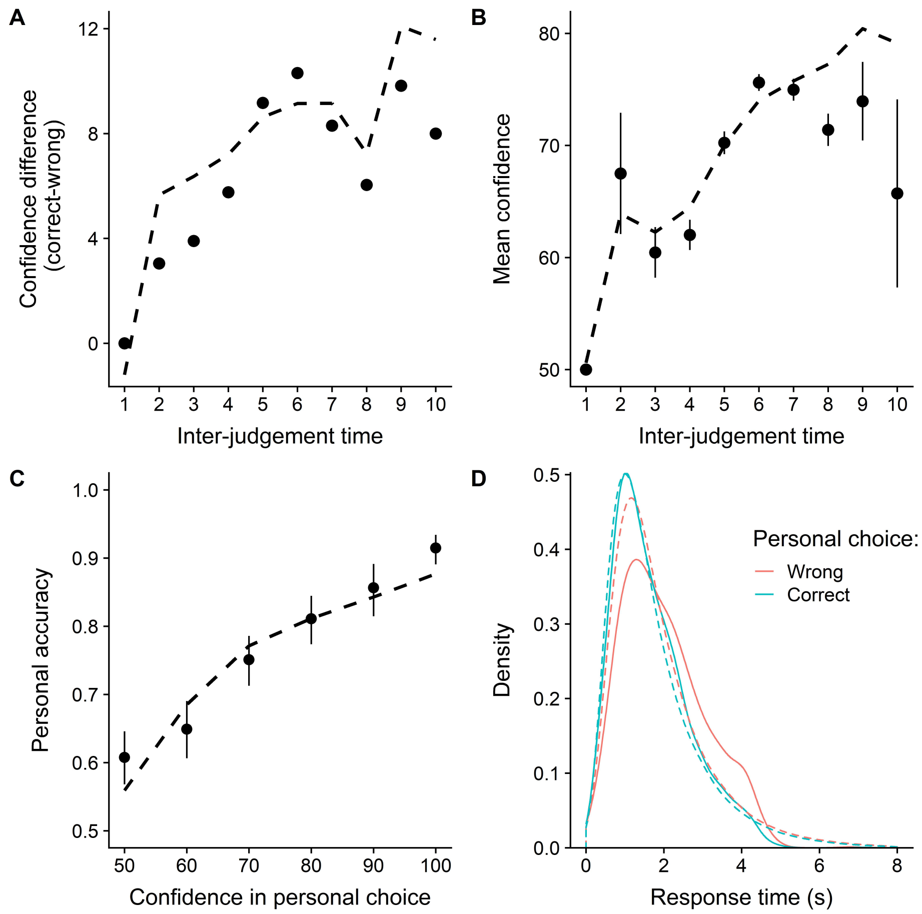

Figure S4: **Results of the 2DSD model.** **(A)** The longer the time between the personal choice and the confidence judgement (interjudgement time), the larger the difference in confidence between participants whose choices were correct vs. incorrect. Dots represent the average confidence judgements for correct choices minus the average confidence judgements for incorrect choices for different interjudgement times. **(B)** The longer the interjudgement time, the higher the reported confidence judgements. Dots represent the mean; error bars represent twice the standard error. **(A–B)** For visualization purposes, interjudgement times are binned by rounding to the closest integer. **(C)** Participants reporting higher confidence were more likely to be correct. Dots and error bars represent mean and 95% CI of the posterior distribution. **(D)** The solid lines represent the observed RT distribution of the personal choice for correct (blue) and incorrect (red) choices. **(A–D)** The dashed lines represent the predictions of the 2DSD model.

Supplementary Tables

Table S1: Bayesian linear regression results

Response Predictor	Estimate	Est.Error	l−95% CI	u−95% CI	Eff.Sample	Rhat
Accuracy						
Intercept (personal choice)	1.1	0.07	0.97	1.23	9657.34	1
Social choice	0.3	0.05	0.2	0.39	32162.95	1
Accuracy						
Intercept	-1.58	0.17	-1.91	-1.25	20461.1	1
Confidence	3.82	0.24	3.35	4.28	20270.94	1
Accuracy						
Intercept (personal choice)	1.65	0.08	1.48	1.81	7563.13	1
RT	-0.16	0.01	-0.18	-0.14	15170.53	1
RT: social choice	0.11	0.01	0.09	0.13	18797	1
Likelihood to change						
Intercept	-3.6	0.18	-3.96	-3.26	7735.1	1
Size of opposing majority	0.62	0.03	0.57	0.67	12889.8	1
RT						
Intercept	6.96	0.23	6.49	7.41	4644.56	1
Confidence	-4.86	0.18	-5.22	-4.5	9740.24	1
Improvement						
Intercept	1.17	0.2	0.78	1.56	22984.38	1
Confidence	-4.27	0.31	-4.88	-3.68	21332.94	1
Improvement						
Intercept (earlier; more accurate)	0.09	0.01	0.08	0.11	3830.29	1
Earlier; less accurate	-0.09	0	-0.09	-0.08	19689.95	1
Later; more accurate	-0.04	0.01	-0.05	-0.03	16925.55	1
Later; less accurate	-0.04	0.01	-0.06	-0.02	17547.86	1

Table S2: Deviance information criterions (DIC) for different versions of the social DDM. The version with the lowerst DIC is indicated in bold.

	No further drift	Drift towards initial choice	Drift towards correct
Neither	79493	76026	77854
Varying start point	76364	74183	74851
Social drift	78058	74275	77286
Both	74200	**71865**	73835

Table S3: Mean paramter estimates and 95% credible intervals of the social DDM for different group sizes.

Model feature (parameter)	Small	Medium	Large
NDT (τ)	0.4 [0.23, 0.56]	0.33 [0.25, 0.41]	0.31 [0.26, 0.37]
Relative start point (a)	4.2 [3.11, 5.35]	3.43 [2.81, 4.07]	3.9 [3.46, 4.37]
Relative start point (b)	0.5 [0.45, 0.54]	0.48 [0.45, 0.51]	0.5 [0.48, 0.52]
Personal drift (δ_p)	0.65 [0.45, 0.86]	0.62 [0.5, 0.75]	0.53 [0.47, 0.59]
Social drift (s)	0.51 [0.23, 0.82]	0.31 [0.24, 0.38]	0.36 [0.3, 0.41]
Social drift (q)	1.75 [1.16, 2.36]	0.93 [0.81, 1.05]	0.66 [0.6, 0.72]
Choice threshold (θ)	3.22 [2.58, 3.9]	3.43 [3.09, 3.77]	3.3 [3.04, 3.56]

Table S4: Differences between parameter estimates for different group sizes. Shown are the mean and the 95% credible intervals.

Model feature (parameter)	Small – Medium	Small – Large	Medium – Large
NDT (τ)	0.06 [-0.12, 0.25]	0.08 [-0.09, 0.26]	0.02 [-0.08, 0.11]
Relative start point (a)	0.77 [-0.48, 2.08]	0.3 [-0.88, 1.51]	-0.47 [-1.25, 0.31]
Relative start point (b)	0.01 [-0.04, 0.07]	-0.01 [-0.06, 0.04]	-0.02 [-0.06, 0.02]
Personal drift (δ_p)	0.03 [-0.2, 0.27]	0.12 [-0.08, 0.33]	0.09 [-0.04, 0.23]
Social drift (s)	0.2 [-0.09, 0.51]	0.15 [-0.13, 0.46]	-0.05 [-0.13, 0.04]
Social drift (q)	0.82 [0.22, 1.44]	1.1 [0.5, 1.71]	0.27 [0.14, 0.41]
Choice threshold (θ)	-0.21 [-0.93, 0.54]	-0.08 [-0.77, 0.65]	0.13 [-0.3, 0.56]

Table S5: The number of groups per group size.

Group size	**Number of groups**	**Number of participants**	**Classification**
3	5	15	Small
7	3	21	Medium
8	1	8	Medium
9	1	9	Medium
10	1	10	Medium
15	3	45	Large
16	1	16	Large
17	1	17	Large
Total:	**16**	**141**	

Table S6: Description of the parameters of the 2DSD model.

Model feature	**Parameter**	**Description**
Nondecision time	NDT	A parameter between 0 and 1 accounting for nondecision time (e.g., motor response time), parameterized as the time relative to an individual's fastest response.
Relative start point	z	Describes the initial evidence state before the evidence sampling process begins.
Predecisional drift rate	$\delta_{pre} = \begin{cases} \delta_{difficult}, & \text{if difficult} \\ \delta_{difficult} + \Delta_{easy}, & \text{if easy} \end{cases}$	The baseline predecisional drift rate for difficult (i.e., 4 or 6 sharks) and easy (i.e., 3 or 7 sharks) trials.
Boundary separation	α	The boundary separation determines how much evidence an individual has to accumulate to make a decision.
Carryover effect	w	A parameter controlling how strongly the predecisional drift rate carries over to the postdecisional drift rate.
Self-confirmation bias	δ_{choice}	A parameter describing the influence of the choice (i.e., being correct or incorrect) on the subsequent drift rate.
Confidence criteria	c_j	Thresholds that divide the evidence space into confidence judgements.

Table S7: 2DSD parameter results

Parameter	Estimate	l−95% CI	u−95% CI	Eff.Sample	Rhat
Nondecision time	0.63	0.56	0.74	2362.88	1
Relative start point	0.53	0.52	0.54	2085.7	1
Predecisional drift rate (intercept, difficult)	0.37	0.33	0.41	1991.81	1
Predecisional drift rate (effect of easy)	0.05	0	0.1	2256.05	1
Boundary separation	2.5	2.45	2.56	2268.78	1
Carryover effect	0.72	0.62	0.83	2354.22	1
Self-confirmation bias	1.64	1.47	1.8	1962.74	1
Confidence criteria 5	3.27	2.46	4.09	1875.05	1
Confidence criteria 4	4.99	4.54	5.44	2444.76	1
Confidence criteria 3	3.83	3.5	4.17	2160.56	1
Confidence criteria 2	3.04	2.74	3.35	2499.86	1
Confidence criteria 1	2.4	2.11	2.72	2605.37	1

REFERENCES AND NOTES

1. L. R. Anderson, C. A. Holt, Information cascades in the laboratory. *Am. Econ. Rev.* **87**, 847–862 (1997).

2. S. Bikhchandani, D. Hirshleifer, I. Welch, Learning from the behavior of others: Conformity, fads, and informational cascades. *J. Eco. Perspect.* **12**, 151–170 (1998).

3. C. Frydman, I. Krajbich, Using Response Times to Infer Others' Beliefs: An Application to Information Cascades (May 8, 2019). Available at SSRN: https://ssrn.com/abstract=2817026.

4. S. Vosoughi, D. Roy, S. Aral, The spread of true and false news online. *Science* **359**, 1146–1151 (2018).

5. J. J. Faria, S. Krause, J. Krause, Collective behavior in road crossing pedestrians: The role of social information. *Behav. Ecol.* **21**, 1236–1242 (2010).

6. I. Welch, Herding among security analysts. *J. Financ. Econ.* **58**, 369–396 (2000).

7. Y.-F. Chen, Herd behavior in purchasing books online. *Comput. Hum. Behav.* **24**, 1977–1992 (2008).

8. M. Battaglini, Sequential voting with abstention. *Games Econ. Behav.* **51**, 445–463 (2005).

9. F. Xiong, Y. Liu, Opinion formation on social media: An empirical approach. *Chaos* **24**, 013130 (2014).

10. J.-L. Deneubourg, S. Aron, S. Goss, J. M. Pasteels, The self-organizing exploratory pattern of the Argentine ant. *J. Insect Behav.* **3**, 159–168 (1990).

11. J. K. Goeree, T. R. Palfrey, B. W. Rogers, R. D. McKelvey, Self-correcting information cascades. *Rev. Econ. Stud.* **74**, 733–762 (2007).

12. D. J. Sumpter, S. C. Pratt, Quorum responses and consensus decision making. *Phil. Trans. R. Soc. B* **364**, 743–753 (2008).

13. C. Chamley, D. Gale, Information revelation and strategic delay in a model of investment. *Econometrica* **62**, 1065–1085 (1994).

14. J. Zhang, Strategic delay and the onset of investment cascades. *Rand J. Econ.* **28**, 188–205 (1997).

15. A. Ziegelmeyer, K. B. My, J.-C. Vergnaud, M. Willinger, Strategic Delay and Rational Imitation in the Laboratory, in *Papers on Strategic Interaction* (Max Planck Institute of Economics, Strategic Interaction Group, 2005).

16. R. Hertwig, T. J. Pleskac, T. Pachur, The Center for Adaptive Rationality, *Taming uncertainty* (MIT Press, 2019).

17. T. J. Pleskac, J. R. Busemeyer, Two-stage dynamic signal detection: A theory of choice, decision time, and confidence. *Psychol. Rev.* **117**, 864–901 (2010).

18. A. Tversky, D. Kahneman, Judgment under uncertainty: Heuristics and biases. *Science* **185**, 1124–1131 (1974).

19. R. Ratcliff, A theory of memory retrieval. *Psychol. Rev.* **85**, 59–108 (1978).

20. M. Usher, J. L. McClelland, The time course of perceptual choice: The leaky, competing accumulator model. *Psychol. Rev.* **108**, 550–592 (2001).

21. R. Ratcliff, P. L. Smith, A comparison of sequential sampling models for two-choice reaction time. *Psychol. Rev.* **111**, 333–367 (2004).

22. R. M. Nosofsky, T. J. Palmeri, An exemplar-based random walk model of speeded classification. *Psychol. Rev.* **104**, 266–300 (1997).

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

24. M. Germar, A. Schlemmer, K. Krug, A. Voss, A. Mojzisch, Social influence and perceptual decision making: A diffusion model analysis. *Pers. Soc. Psychol. Bull.* **40**, 217–231 (2014).

25. U. Toelch, F. Panizza, H. R. Heekeren, Norm compliance affects perceptual decisions through modulation of a starting point bias. *R. Soc. Open Sci.* **5**, 171268 (2018).

26. R. Ratcliff, G. McKoon, The diffusion decision model: Theory and data for two-choice decision tasks. *Neural Comput.* **20**, 873–922 (2008).

27. S. D. Brown, A. Heathcote, The simplest complete model of choice response time: Linear ballistic accumulation. *Cogn. Psychol.* **57**, 153–178 (2008).

28. A. Voss, K. Rothermund, J. Voss, Interpreting the parameters of the diffusion model: An empirical validation. *Mem. Cognit.* **32**, 1206–1220 (2004).

29. F. P. Leite, R. Ratcliff, What cognitive processes drive response biases? A diffusion model analysis. *Judgm. Decis. Mak.* **6**, 651–687 (2011).

30. T. J. Pleskac, J. Cesario, D. J. Johnson, How race affects evidence accumulation during the decision to shoot. *Psychon. Bull. Rev.* **25**, 1301–1330 (2018).

31. I. Krajbich, A. Rangel, Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proc. Natl. Acad. Sci. U.S.A.* **108**, 13852–13857 (2011).

32. B. G. Galef, K. N. Laland, Social learning in animals: Empirical studies and theoretical models. *BioScience* **55**, 489–499 (2005).

33. S. Yu, T. J. Pleskac, M. D. Zeigenfuse, Dynamics of postdecisional processing of confidence. *J. Exp. Psychol. Gen.* **144**, 489–510 (2015).

34. B. Latané, The psychology of social impact. *Am. Psychol.* **36**, 343–356 (1981).

35. D. J. Spiegelhalter, N. G. Best, B. P. Carlin, A. Van Der Linde, Bayesian measures of model complexity and fit. *J. R. Stat. Soc. Series B Stat. Methodol.* **64**, 583–639 (2002).

36. J. Klayman, Varieties of confirmation bias. *Psychol. Learn. Motiv.* **32**, 385–418 (1995).

37. R. S. Nickerson, Confirmation bias: A ubiquitous phenomenon in many guises. *Rev. Gen. Psychol.* **2**, 175–220 (1998).

38. B. Jayles, H.-R. Kim, R. Escobedo, S. Cezera, A. Blanchet, T. Kameda, C. Sire, G. Theraulaz, How social information can improve estimation accuracy in human groups. *Proc. Natl. Acad. Sci. U.S.A.* **114**, 12620–12625 (2017).

39. R. P. Larrick, J. B. Soll, Intuitions about combining opinions: Misappreciation of the averaging principle. *Manage. Sci.* **52**, 111–127 (2006).

40. A. Novaes Tump, M. Wolf, J. Krause, R. H. J. M. Kurvers, Individuals fail to reap the collective benefits of diversity because of over-reliance on personal information. *J. R. Soc. Interface* **15**, 20180155 (2018).

41. I. Yaniv, E. Kleinberger, Advice taking in decision making: Egocentric discounting and reputation formation. *Organ. Behav. Hum. Decis. Process.* **83**, 260–281 (2000).

42. D. J. Koehler, T. A. Beauregard, Illusion of confirmation from exposure to another's hypothesis. *J. Behav. Decis. Mak.* **19**, 61–78 (2006).

43. R. Bond, Group size and conformity. *Group Process. Intergroup Relat.* **8**, 331–354 (2005).

44. S. Milgram, L. Bickman, L. Berkowitz, Note on the drawing power of crowds of different size. *J. Pers. Soc. Psychol.* **13**, 79–82 (1969).

45. S. S. Stevens, On the psychophysical law. *Psychol. Rev.* **64**, 153–181 (1957).

46. R. H. J. M. Kurvers, M. Wolf, J. Krause, Humans use social information to adjust their quorum thresholds adaptively in a simulated predator detection experiment. *Behav. Ecol. Sociobiol.* **68**, 449–456 (2014).

47. B. Çelen, S. Kariv, Distinguishing informational cascades from herd behavior in the laboratory. *Am. Econ. Rev.* **94**, 484–498 (2004).

48. J. R. G. Dyer, A. Johansson, D. Helbing, I. D. Couzin, J. Krause, Leadership, consensus decision making and collective behaviour in humans. *Philos. Trans. R. Soc. B. Biol. Sci.* **364**, 781–789 (2009).

49. R. H. J. M. Kurvers, M. Wolf, M. Naguib, J. Krause, Self-organized flexible leadership promotes collective intelligence in human groups. *R. Soc. Open Sci.* **2**, 150222 (2015).

50. I. Watts, M. Nagy, T. Burt de Perera, D. Biro, Misinformed leaders lose influence over pigeon flocks. *Biol. Lett.* **12**, 20160544 (2016).

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

52. R. Hertwig, Tapping into the wisdom of the crowd—with confidence. *Science* **336**, 303–304 (2012).

53. B. Bahrami, K. Olsen, D. Bang, A. Roepstorff, G. Rees, C. Frith, What failure in collective decision-making tells us about metacognition. *Philos. Trans. R. Soc. Lond B Biol. Sci.* **367**, 1350–1365 (2012).

54. D. Bang, C. D. Frith, Making better decisions in groups. *R. Soc. Open Sci.* **4**, 170193 (2017).

55. L. Chittka, P. Skorupski, N. E. Raine, Speed–accuracy tradeoffs in animal decision making. *Trends Ecol. Evol.* **24**, 400–407 (2009).

56. M. Moussaïd, M. Kapadia, T. Thrash, R. W. Sumner, M. Gross, D. Helbing, C. Hölscher, Crowd behaviour during high-stress evacuations in an immersive virtual environment. *J. R. Soc. Interface* **13**, 20160414 (2016).

57. E. Danchin, L.-A. Giraldeau, T. J. Valone, R. H. Wagner, Public information: From nosy neighbors to cultural evolution. *Science* **305**, 487–491 (2004).

58. P.-C. Bürkner, brms: An R package for Bayesian multilevel models using Stan. *J. Stat. Softw.* **80**, 1–28 (2017).

59. A. Diederich, J. R. Busemeyer, Simple matrix methods for analyzing diffusion models of choice probability, choice response time, and simple response time. *J. Math. Psychol.* **47**, 304–322 (2003).

60. B. M. Turner, P. B. Sederberg, S. D. Brown, M. Steyvers, A method for efficiently sampling from distributions with correlated dimensions. *Psychol. Methods* **18**, 368–384 (2013).

61. R Core Team, *R: A Language and Environment for Statistical Computing* (R Foundation for Statistical Computing, 2019).

62. Stan Development Team, RStan: The R Interface to Stan (2018). R package version 2.18.2.