On the Demand for Mental Models

Julian Matthes & Katharina Momsen

Heidelberg University

May 27, 2025

Motivation

(a) Sports Statistics

(b) Technical Analysis

Figure: Who responds to these headlines?

Motivation

Forming beliefs in an uncertain, complex environment is comprised of two parts:

- Forming a subjective models of the data generating process, and
- gathering and evaluating historical data given that model.

$\Rightarrow$ Research agenda: How do people approach the tradeoff between allocating time and effort to either task?

$\Rightarrow$ RQ here: In a prediction task, how do subjects value "interpretations" of historical data against more historical data or an informative signal about outcome?

Literature on Subjective Mental Models

Mental models take a central role in belief formation and decision making

- Kendall and Oprea [2024]: People form mental models, prefer simple ones, want to communicate them
- Kendall and Charles [2024]: Exposure to contradictory models can move beliefs in different directions, given the same data
- Barron and Fries [2024]: People are better persuaded by models that have a good fit with historical data
- Ambuehl and Thysen [2024]: Heterogeneity in preferences for models (types: caution, wishful thinking, historical fit)

Emerging literature focuses on how selection between/preferences for models

- Selection criteria: Schwartzstein and Sunderam [2021], Aina [2021], Spiegler [2016], Ambuehl and Thysen [2024]
- Model competition: Eliaz and Spiegler [2020], Aina and Schneider [2025], Ba [2024]

More Literature

- Wishful Thinking: Barron [2021], Caballero and López Pérez [2020], Mayraz [2011], Lahav and Santo [2022], Caplin and Leahy [2019]
- Demand for Information: Ambuehl and Li [2018], Eliaz and Schotter [2010]
- News Demand: Chopra et al. [2024]
- Reaction to interpretations/explanations/models: Graeber et al. [2024b], Graeber et al. [2024a], Grass et al. [2025]

Design overview

y	NB		
	d_+	d_-	*aux*
1	1	0	1
1	1	0	1
1	1	0	1
1	1	0	1
1	0	0	0
1	0	0	1
0	0	1	1
0	0	1	1
0	0	1	1
0	0	1	1
0	0	0	1
0	0	0	0
?	**1**	**1**	**1**

Table: Data Table

Task: Assess the probability that ? $= 1$.

Payoff Treatments:

- Group A(ccuracy): Incentivized to match realization of ? (binarized procedure)
- Group B(onus): Incentivized to match realization of ? (binarized procedure) $+$ Bonus if ?$=1$

Message Treatments:

- Subjects see messages conveying interpretations before predicting.
- Subjects can uncover a message from another participant XOR more data / informative signal about ?.

Procedures

- Programmed in otree & run on Prolific with US-subjects
- May 2024 and January 2025
- IRB-approval & pre-registration
- approx. 90 subjects per treatment, 1154 total
- Receivers earned on average $4.16, spent 20 minutes on the experiment

Questions and Design

Q1 Does exposure to interpretations move assessments and certainty?

-> Impact of message treatments on predictions and reported certainty.

Q2 Is there demand for interpretations when it comes at the cost of acquiring “hard information”?

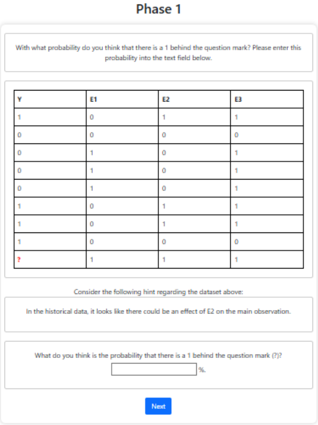
-> Choice between seeing another message XOR more data/an informative signal.

Q3 Is updating in response to or demand for interpretations guided by wishful thinking?

-> Impact of payoff treatments in both predictions and message demand.

Study 1/2: Phase 1

- Message treatments:
  NoMess: Subjects see no message
  SoftMess: "It looks like there may be an effect of E1 on the outcome (?)."
  StrongMess: "Whenever E1 is 1, Y is also equal to 1."
  50Mess: "Y is 1 exactly half of the time."
- Payoff treatments:
  Accuracy, Bonus.


Phase 1

With what probability do you think that there is a 1 behind the question mark? Please enter this probability into the text field below.

Y	E1	E2	E3
1	0	1	1
0	0	0	0
0	1	0	1
0	1	0	1
0	1	0	1
1	0	1	1
1	0	1	1
1	0	0	0
?	1	1	1

Consider the following hint regarding the dataset above:

In the historical data, it looks like there could be an effect of E2 on the main observation.

What do you think is the probability that there is a 1 behind the question mark (?)?

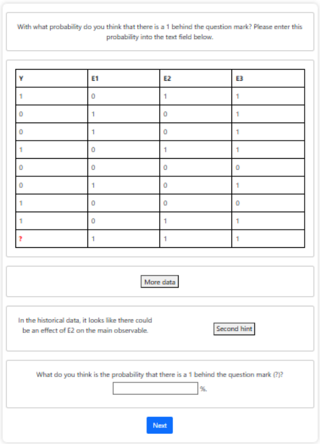
%.

Next

Study 1: Phase 2

- Message treatments: NoMess, SoftMess, StrongMess.
- Payoff treatments: Accuracy, Bonus.

Phase 2



With what probability do you think that there is a 1 behind the question mark? Please enter this probability into the text field below.

Y	E1	E2	E3
1	0	1	1
0	1	0	1
0	1	0	1
1	0	1	1
0	0	0	0
0	1	0	1
1	0	0	0
1	0	1	1
?	1	1	1

More data

In the historical data, it looks like there could be an effect of E2 on the main observable.

Second hint

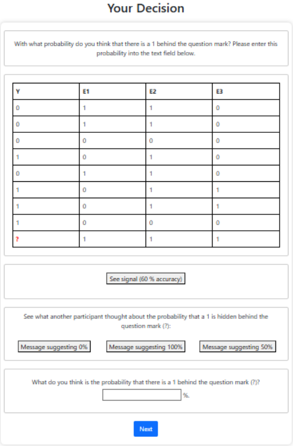
What do you think is the probability that there is a 1 behind the question mark (?)?

%.

Next

Study 2

- Signal treatments:
  Acc60: 60 percent accuracy,
  Acc90: 90 percent accuracy.
- Payoff treatments:
  Accuracy, Bonus.



Your Decision

With what probability do you think that there is a 1 behind the question mark? Please enter this probability into the text field below.

Y	E1	E2	E3
0	1	1	0
0	1	1	0
0	0	0	0
1	0	1	0
0	1	1	0
1	0	1	1
1	0	1	1
1	0	0	0
?	1	1	1

See signal (60 % accuracy)

See what another participant thought about the probability that a 1 is hidden behind the question mark (?):

Message suggesting 0% | Message suggesting 100% | Message suggesting 50%

What do you think is the probability that there is a 1 behind the question mark (?)?

%.

Next

Impact of Messages

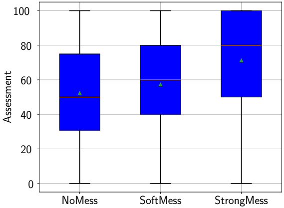


Figure: Assessments

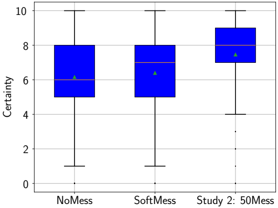


Figure: Certainty

Messages impact assessments and certainty.

Impact of Messages

Wishful Thinking?

	Assessment (w/ contr.)	Assessment	Cert.	Cert. (w/ contr.)
Bonus	-1.048	$\boxed{-0.603}$	0.006	$\boxed{-0.001}$
	(1.886)	(1.848)	(0.200)	(0.190)
SoftMess	5.074**	2.807	0.234	-0.001
	(2.307)	(2.289)	(0.244)	(0.235)
StrongMess	18.969***	12.829***	1.052***	0.562**
	(2.307)	(2.352)	(0.244)	(0.241)
Group Var	0.466***	0.505***	2.029***	2.060***
	(0.061)	(0.066)	(0.180)	(0.184)
Observations	1554	1554	1554	1554
Residual Std. Error	21.552 (df=1550)	20.307 (df=1535)	1.251 (df=1550)	1.169 (df=1535)

Note: *p<0.1; **p<0.05; ***p<0.01

Table: Payoff Treatment Effect on Assessments and Certainty.

Demand for Messages

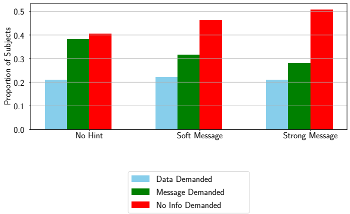


Figure: Study 1

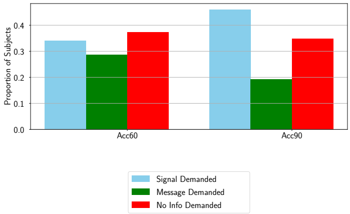


Figure: Study 2

Positive demand for messages in all treatments.

Demand for Messages

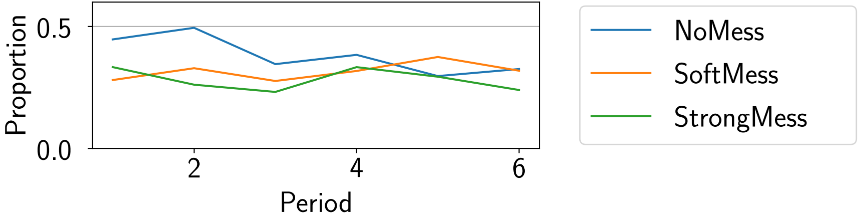


Figure: Message Demand over Time

Positive demand for messages in all treatments and all periods.

Demand for Messages

Wishful Thinking?

	Message Demand
	(1)
Bonus	-0.062**
	(0.030)
Assessment	0.000
	(0.000)
Certainty	-0.011*
	(0.005)
SoftMess	-0.095**
	(0.038)
StrongMess	-0.159***
	(0.039)
Group Var	0.553***
	(0.069)
Observations	1554
Residual Std. Error	0.324 (df=1532)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table: Study 1: Message Demand

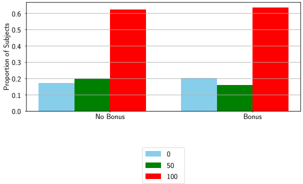


Figure: Study 2: Message Choice

Conclusion

Results:

- R1 Exposure to interpretations of data moves assessments and subjective certainty.
- R2 Subjects demand interpretations even at the cost of missing out on hard information.
- R3 No evidence of wishful thinking in interpretation acquisition or reaction.

Moving on:

- How about motivated interpretations of ego-relevant data? (actually measure impact of oddly specific sports statistics on betting behavior of fans?)
- Theory on demand for interpretations in uncertain environments?

References I

Chiara Aina. Tailored stories. Technical report, Mimeo, 2021.

Chiara Aina and Florian Schneider. Weighting competing models. 2025.

Sandro Ambuehl and Shengwu Li. Belief updating and the demand for information. *Games and Economic Behavior*, 109:21–39, 2018.

Sandro Ambuehl and Heidi Thysen. Competing causal interpretations. Technical report, 2024.

Cuimin Ba. Robust model misspecification and paradigm shifts. 2024.

Kai Barron. Belief updating: does the 'good-news, bad-news' asymmetry extend to purely financial domains? *Experimental Economics*, 24(1):31–58, 2021.

References II

Kai Barron and Tilman Fries. Narrative persuasion. Technical report, WZB Discussion Paper, 2024.

Adrián Caballero and Raúl López Pérez. Economic models of optimism: What does the evidence say? 2020.

Andrew Caplin and John V Leahy. Wishful thinking. Technical report, National Bureau of Economic Research, 2019.

Felix Chopra, Ingar Haaland, and Christopher Roth. The demand for news: Accuracy concerns versus belief confirmation motives. *The Economic Journal*, 134(661):1806–1834, 2024.

Kfir Eliaz and Andrew Schotter. Paying for confidence: An experimental study of the demand for non-instrumental information. *Games and Economic Behavior*, 70(2):304–324, 2010.

References III

Kfir Eliaz and Ran Spiegler. A model of competing narratives. *American Economic Review*, 110(12):3786–3816, 2020.

Thomas Graeber, Christopher Roth, and Constantin Schesch. Explanations. Technical report, CESifo Working Paper, 2024a.

Thomas Graeber, Christopher Roth, and Florian Zimmermann. Stories, statistics, and memory. *The Quarterly Journal of Economics*, 139(4):2181–2225, 2024b.

Paul Grass, Philipp Schirmer, and Malin Siemers. Sticky models. Technical report, ECONtribute Discussion Paper, 2025.

Chad Kendall and Ryan Oprea. On the complexity of forming mental models. Technical report, 2024.

Chad W Kendall and Constantin Charles. Causal narratives. Technical report, National Bureau of Economic Research, 2024.

References IV

Yaron Lahav and Or Santo. Wishful betting. *Economics Letters*, 218:110778, 2022.

Guy Mayraz. Wishful thinking. *Available at SSRN 1955644*, 2011.

Joshua Schwartzstein and Adi Sunderam. Using models to persuade. *American Economic Review*, 111(1):276–323, 2021.

Ran Spiegler. Bayesian networks and boundedly rational expectations. *The Quarterly Journal of Economics*, 131(3): 1243–1290, 2016.

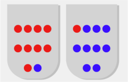
Urn Task

Messages

A message is a short text from another participant who also assessed the probability that there is a 1 behind the question mark (?) in the dataset that is presented to you. You can choose between three different messages. Each message points out a pattern in the visible part of the dataset and thus may be helpful to you in interpreting the dataset. Note, however, that the other participant did not have more information about the number behind the question mark (?) than you.

Signals

The signal can help you assess whether there is a 0 or a 1 behind the question mark (?). If you choose to reveal the signal, you will see either a red ball or a blue ball. If the ball is red, this means that the number behind the question mark (?) is more likely a 0 than a 1. If the ball is blue, the number behind the question mark (?) is more likely a 1 than a 0. The signal is generated as follows: There are two urns like in the figure below. Urn Zero contains 1 blue balls and 9 red balls, and Urn One contains 9 blue balls and 1 red balls. If the number behind the question mark (?) is a 0, a ball is drawn from Urn Zero. Otherwise, a ball is drawn from the Urn One.



Urn Zero Urn One

Figure: Signal Instructions

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Payoffs

- Updating: One round is payoff-relevant
  - Coin toss decides whether a 0 or a 1 is behind question mark.
  - Subject's assessment of the probability that there is a 1 hidden. q
    - Coin toss is a 1: Payoff = USD 3 with a probability of $1-(1-q)^2$, 0 with the complementary probability
    - Coin toss is a 0: USD 3 with a probability of $1-q^2$, 0 with the complementary probability
- Bonus: Payoff of USD 1.5 for a coin toss resulting in a 1.

back

Full Output: Main Regression

	(1)	(2)	(3)	(4)
Age		-0.120		-0.001
		(0.081)		(0.008)
Assessment				0.022***
				(0.002)
Bonus		-0.605		
		(1.847)		
C(DV1)[T.Yes]		-2.796		0.358
		(2.230)		(0.229)
C(Male)[T.1]		-3.299*		0.328
		(1.957)		(0.201)
C(Male)[T.98]		1.485		1.190
		(14.824)		(1.523)
C(Male)[T.99]		18.163*		0.504
		(10.675)		(1.097)
C(Simple2)[T.Yes]		3.085		0.017
		(3.912)		(0.402)
Certainty		3.709***		
		(0.323)		
DV2		-0.274		0.041
		(0.404)		(0.041)
DecTime		0.002		-0.003***
		(0.014)		(0.001)
Group Var	0.465***	0.512***	2.025***	2.054***
	(0.061)	(0.067)	(0.180)	(0.184)
MessageHelpful		0.992***		0.043
		(0.375)		(0.038)
MessageMisleading		-0.673		0.023
		(0.433)		(0.044)
Intercept	52.330***	47.947***	6.157***	2.757***
	(1.626)	(7.115)	(0.172)	(0.710)
Minus		-4.000***		-0.074
		(1.402)		(0.086)
Period		0.508		-0.065***
		(0.377)		(0.024)
Plus		0.460		-0.077
		(1.402)		(0.086)
PolPref		-0.209		0.050
		(0.337)		(0.035)
RiskPref		-0.777*		0.190***
		(0.421)		(0.043)
Simple1		-1.223***		0.080*
		(0.405)		(0.042)
SoftMess	5.068**	2.809	0.234	-0.001
	(2.306)	(2.287)	(0.244)	(0.235)
StrongMess	18.975***	12.859***	1.052***	0.563**
	(2.306)	(2.350)	(0.244)	(0.241)
Observations	1554	1554	1554	1554
Residual Std. Error	21.552 (df=1551)	20.196 (df=1533)	1.250 (df=1551)	1.169 (df=1534)

Note: *p<0.1; **p<0.05; ***p<0.01

▸ back

Full Output: Regression Info Demand

	Dependent variable: MessAdd
	(1)
Age	0.001
	(0.001)
Assessment	0.000
	(0.000)
Bonus	-0.062**
	(0.030)
C(DV1)[T.Yes]	-0.064*
	(0.037)
C(Male)[T.1]	-0.042
	(0.032)
C(Male)[T.98]	-0.172
	(0.245)
C(Male)[T.99]	-0.209
	(0.176)
C(Simple2)[T.Yes]	0.052
	(0.065)
Certainty	-0.011*
	(0.005)
DV2	0.011
	(0.007)
DecTime	0.000
	(0.000)
Group Var	0.553***
	(0.069)
MessageHelpful	0.041***
	(0.006)
MessageMisleading	0.015**
	(0.007)
Intercept	0.002
	(0.119)
Minus	-0.053**
	(0.023)
Period	0.004
	(0.006)
Plus	-0.046**
	(0.023)
PolPref	-0.007
	(0.006)
RiskPref	-0.003
	(0.007)
Simple1	0.016**
	(0.007)
SoftMess	-0.095**
	(0.038)
StrongMess	-0.159***
	(0.039)
Observations	1554
Residual Std. Error	0.324 (df=1532)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table: Table 3 full

back

Tables

Table: Deterministic Datasets

(a) Balanced

y	**E**		
	E_+	E_-	E_0
Hidden			
1	1	0	1
1	0	0	1
0	0	1	1
0	0	0	1
Visible			
1	1	0	1
1	1	0	1
1	1	0	1
1	0	0	0
0	0	1	1
0	0	1	1
0	0	1	1
0	0	0	0
Assessment			
?	**1**	**1**	**1**

(b) Pro

y	**E**		
	E_+	E_-	E_0
Hidden			
1	1	0	1
1	0	0	1
0	0	1	1
0	0	1	1
Visible			
1	1	0	1
1	1	0	1
1	1	0	1
1	0	0	0
0	0	1	1
0	0	0	1
0	0	1	1
0	0	0	0
Assessment			
?	**1**	**1**	**1**

(c) Con

y	**E**		
	E_+	E_-	E_0
Hidden			
1	1	0	1
1	1	0	1
0	0	1	1
0	0	0	1
Visible			
1	1	0	1
1	1	0	1
1	0	0	0
1	0	0	1
0	0	1	1
0	0	1	1
0	0	1	1
0	0	0	0
Assessment			
?	**1**	**1**	**1**

back