Complex disclose

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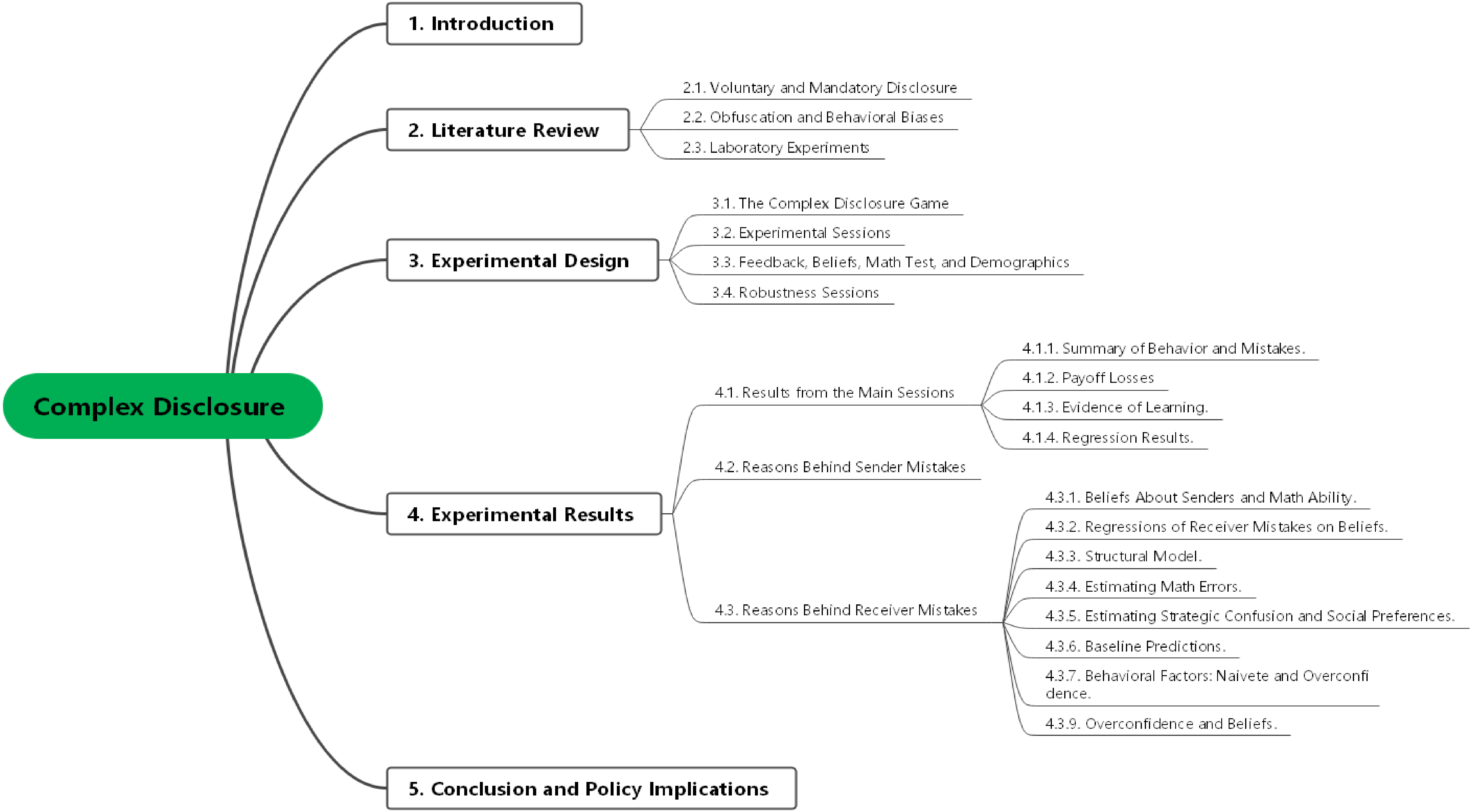
Abstract.

We present evidence that unnecessarily complex disclosure can result from strategic incentives to shroud information.

In our laboratory experiment, senders can choose how complex to make their reports. We find that senders use complex disclosure more than half the time. This obfuscation is profitable because receivers make systematic mistakes in assessing complex reports.

Regression and structural analysis suggest that these **mistakes** could be driven by receivers who are **naive** about the strategic use of complexity or **overconfident** about their ability to process complex information.



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I Introduction

背景描述

- **Firms are often required to disclose contract terms and other relevant information to consumers.**
  - Credit card companies are required to disclose interest rates.
  - Tech companies are required to disclose privacy policies.
  - Public fifirms are required to disclose financial performance.
- **Some of these disclosures are complex by necessity simply because fifirms need to provide very detailed information. However, because fifirms have the ability to manipulate the complexity of their reports, some of these disclosures may be far more complex than they need to be.**
  - Credit card companies can present payment schedules, penalties, and fees clearly or bury potentially important details in the fifine print.
  - Privacy policies can be written in easy-to-understand language or shrouded in pages of complex legalese.
  - Public fifirms make fifinancial disclosures, they can summarize them in several paragraphs or run them as long as 257 pages.

对于企业来说

The extent to which firms can exploit consumers by increasing complexity depends crucially on how consumers respond when they observe complex information.

If consumers are sufficiently skeptical about firms that use complex disclosures and account for this in their decision-making process, then firms that offer better terms or higher quality products will want to present this information as clearly and simply as possible to prevent themselves from being mistaken for worse firms.

As a result, we would expect only the worst firms to use complex disclosures, which is similar to the “unraveling” results in voluntary disclosure.

对于消费者来说

However, systematic mistakes by consumers when facing complex reports can give rise to strategic incentives to complexify, motivating companies to choose complexity over simplicity in their disclosures.

In reality, it is difficult to determine if consumers are sufficiently skeptical about firms that use complex disclosures and account for this in their decision-making process because it is hard to discern whether disclosures are complex by necessity or the outcome of firms strategically choosing to make information unnecessarily complex.

To overcome this difficulty, we designed a laboratory experiment to study the strategic use of complexity in a controlled setting. In our experiment, complexity arises only from its strategic use, the conflicting interests of senders and receivers are clear, the amount and overuse of complexity are quantifiable, and the beliefs of agents are easily elicited.

III Experimental Design

3.2. Experimental Sessions

Our sessions were conducted at the Computer Laboratory for Experimental Research (CLER) facility at the Harvard Business School. In this laboratory, subjects are separated with dividers, and each subject was provided with a personal computer terminal. Subjects do not have to be Harvard University students, so we restricted subjects to be no more than 25 years old in order for the subject pool to be more comparable with existing studies that recruit undergraduate students. The software used to run the experiments was the z-Tree software package.

Each session consisted of 30 rounds of the disclosure game. In each round, subjects were randomly matched into pairs. Each subject could be matched with any other subject in the session and was equally likely to be paired with any given subject.

3.1. The Complex Disclosure Game

Player A (sender)

Secret number **b** b= {1,2,……, 9,10}

chose a complex rate **c** (report length)

c={1,2,……19,20}

The computer program then randomly selected c integers between −10 and 10 until those numbers added up to the true state b.

Example of a report with maximum length (20) b=2

8	**-3**	**-1**	**1**	**-3**
9	0	-4	-3	8
1	0	-7	-6	0
-1	4	-6	-1	6

Player B (receiver)

receivers were asked to make a guess **a** of the secret number b, and this guess could be any integer between 1 and 10. The receiver had 60 seconds to view the sender's report and make a guess.

eg:

8	-3	-1	1	-3
9	0	-4	-3	8
1	0	-7	-6	0
-1	4	-6	-1	6

Receiver and sender payoffs, denominated in experimental currency units (ECUs), 150ecu=1$

Payoffs S, R	Secret number: 1	Secret number: 2	Secret number: 3	Secret number: 4	Secret number: 5	Secret number: 6	Secret number: 7	Secret number: 8	Secret number: 9	Secret number: 10
Guess: 1	-54,110	-54,102	-54,90	-54,75	-54,57	-54,38	-54,17	-54,-6	-54,-29	-54,-54
Guess: 2	-29,102	-29,110	-29,102	-29,90	-29,75	-29,57	-29,38	-29,17	-29,-6	-29,-29
Guess: 3	-6,90	-6,102	-6,110	-6,102	-6,90	-6,75	-6,57	-6,38	-6,17	-6,-6
Guess: 4	17,75	17,90	17,102	17,110	17,102	17,90	17,75	17,57	17,38	17,17
Guess: 5	38,57	38,75	38,90	38,102	38,110	38,102	38,90	38,75	38,57	38,38
Guess: 6	57,38	57,57	57,75	57,90	57,102	57,110	57,102	57,90	57,75	57,57
Guess: 7	75,17	75,38	75,57	75,75	75,90	75,102	75,110	75,102	75,90	75,75
Guess: 8	90,-6	90,17	90,38	90,57	90,75	90,90	90,102	90,110	90,102	90,90
Guess: 9	102,-29	102,-6	102,17	102,38	102,57	102,75	102,90	102,102	102,110	102,102
Guess: 10	110,-54	110,-29	110,-6	110,17	110,38	110,57	110,75	110,90	110,102	110,110

3.3. Feedback, Beliefs, Math Test, and Demographics

Subjects were told four pieces of information after each round:
(1)the actual secret number,
(2) the report length chosen by the sender,
(3) the receiver's guess of the secret number,
and (4) their own payoff.
After all subjects pressed the "OK" button on the screen containing this feedback, the next round began. To reduce social considerations, subjects in the feedback treatment were not told the payoff for the other player in their pairing though it could be deduced using the payoff table. In addition, between rounds, subjects only received feedback about their pairing, not all pairings in the session.

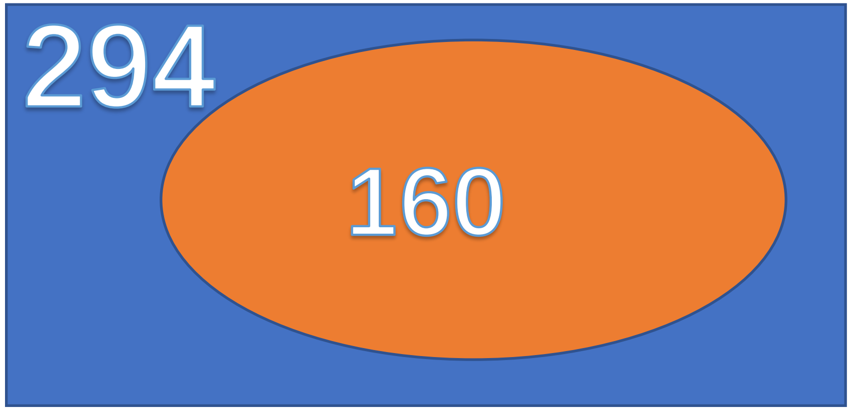
Once all rounds were completed, subjects were asked questions about their beliefs of how other subjects played in their session.

First, subjects were asked to guess the average report length that senders chose for each secret number.
Second, subjects were asked to guess the average secret number when the sender chose complexity levels between 1 and 5, between 6 and 10, between 11 and 15, and between 16 and 20.

The purpose of these questions was to assess whether subject beliefs about sender strategies influenced their decisions as receivers.

Part of subjects were asked to complete a four-question math test after answering the two belief questions.

After completing the math test, subjects answered two additional belief questions.
First, they were asked to guess the number of questions on the math test (from zero to four) that they thought they answered correctly.
Second, they were asked to guess the average number of questions they thought others answered correctly.



IV Experimental Results

- **4.1. Results from the Main Sessions**
  - 4.1.1. Summary of Behavior and Mistakes.
  - 4.1.2. Payoff Losses
  - 4.1.3. Evidence of Learning.
  - 4.1.4. Regression Results.

Table 1. Summary of Subject Characteristics (Main Sessions)

Variable	N	Mean	Standard deviation
Number of subjects in the session	294	10.680	2.554
Feedback provided (dummy)	294	1.000	0.000
Male (dummy)	293	0.410	0.493
Undergraduate (dummy)	293	0.720	0.450
Native English speaker (dummy)	290	0.852	0.356
Friend in the session (dummy)	293	0.143	0.351

Notes. Observation is per subject. Value is missing if demographic information not provided by the subject.

4.1.1. Summary of Behavior and Mistakes.

Table 2. Summary of Sender Choices of Complexity by Secret Number (Main Sessions)

		Sender choice of complexity			High complexity (length ≥15)	Low complexity (length ≤5)
Secret number	N	Mean	Median	Standard deviation	Mean	Mean
1	449	15.626	20	6.619	0.728	0.145
2	444	15.782	20	6.157	0.721	0.115
3	464	13.983	17	6.837	0.616	0.19
4	422	11.969	13	7.218	0.486	0.275
5	433	10.607	10	7.13	0.390	0.344
6	453	8.243	6	6.914	0.254	0.455
7	424	6.748	4	6.664	0.198	0.583
8	427	5.286	2	6.288	0.141	0.71
9	447	4.879	1	6.197	0.128	0.729
10	447	3.832	1	5.622	0.094	0.796
Total	4,410	9.728	9	7.86	0.378	0.432

Figure 1. (Color online) Frequency and Average Sender Choice of Complexity by Secret Number

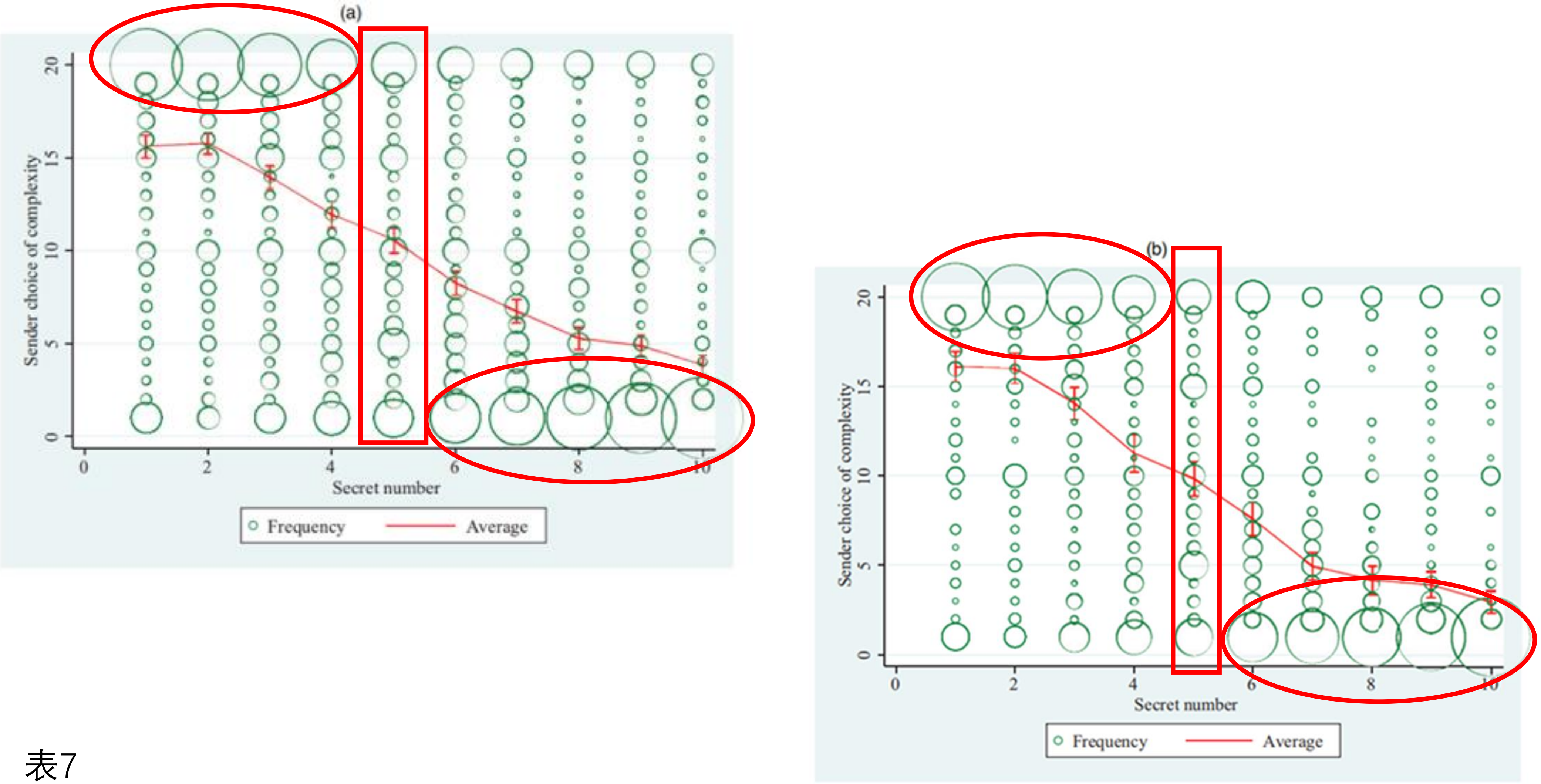


表7

Notes. (a) With 95% confidence intervals (main sessions). (b) In the second half of rounds with 95% confidence intervals (main sessions).

Table 3. Summary of Receiver Guesses by Secret Number (Main Sessions)

Secret number	N	Receiver guess: Mean	Receiver guess: Median	Receiver guess: Standard deviation	Receiver mistake bias (guess-truth): Mean	Receiver mistake size (|guess-truth|): Mean	Percentage of receiver decisions hitting time limit: Mean	Conditional on receiver decision before time limit — Receiver mistake bias (guess-truth): Mean	Conditional on receiver decision before time limit — Receiver mistake size (|guess-truth|): Mean
1	449	2.183	1	2.326	1.183	1.183	5.57	0.946	0.946
2	444	2.923	2	2.209	0.936	1.045	8.11	0.659	0.777
3	464	3.399	3	1.462	0.399	0.601	5.39	0.328	0.492
4	422	4.232	4	1.458	0.232	0.611	3.08	0.191	0.538
5	433	5.169	5	1.378	0.169	0.566	3.23	0.146	[illegible]
6	453	6.031	6	1.167	0.031	0.446	3.97	0.051	0.377
7	424	6.887	7	1.234	−0.113	0.424	2.12	−0.067	0.376
8	427	7.724	8	1.289	−0.276	0.407	1.17	−0.237	0.37
9	447	8.633	9	1.377	−0.367	0.438	2.01	−0.311	0.379
10	447	9.597	10	1.574	−0.403	0.403	0.67	−0.372	0.372
Total	4,410	5.663	6	2.885	0.182	0.614	3.56	0.128	0.509

0.370~0.379

Table 4. Summary of Receiver Guess by Sender Choice of Complexity (Main Sessions)

Complexity	N	Secret number		Receiver guess	Receiver mistake bias (guess-truth)	Receiver mistake size (|guess-truth|)	Percentage hitting time limit	Response time if before time limit	Receiver mistake bias (guess-truth)	Receiver mistake size (|guess-truth|)
		All receiver decisions Mean values							Conditional on receiver decision before time limit mean values	
1	1,259	7.504	>	7.466	−0.038	0.243	0.40	9.15	−0.038	0.236
2	214	6.967	>	6.925	−0.042	0.257	0.00	8.95	−0.042	0.257
3	140	6.429	>	6.407	−0.021	0.15	0.00	13.21	−0.021	0.150
4	104	5.962	>	5.885	−0.077	0.135	0.00	13.35	−0.077	0.135
5	190	5.600	<	5.684	0.084	0.179	0.00	18.15	0.084	0.179
6	91	5.527	<	5.582	0.055	0.231	1.10	18.85	0.089	0.200
7	89	5.685	>	5.629	−0.056	0.146	1.12	21.5	−0.023	0.114
8	117	5.325	>	5.299	−0.026	0.402	0.85	23.67	−0.052	0.379
9	74	4.932	<	5.068	0.135	0.405	0.00	25.45	0.135	0.405
10	263	5.54	>	5.388	−0.152	0.479	1.90	28.77	−0.143	0.438
11	42	5.500	>	5.476	−0.024	0.595	2.38	34.25	0.049	0.537
12	69	4.87	>	4.783	−0.087	0.841	1.45	35.54	0.000	0.765
13	54	4.778	<	5.222	0.444	0.778	0.00	35.56	0.444	0.778
14	39	4.974	<	5.513	0.538	0.795	2.56	37.08	0.632	0.737
15	190	4.384	<	4.463	0.079	0.753	3.16	36.55	0.071	0.712
16	71	3.592	<	4.000	0.408	0.662	7.04	37.21	0.273	0.424
17	90	4.467	<	4.789	0.322	1.033	5.56	40.32	0.306	0.847
18	96	4.292	<	4.573	0.281	1.01	9.38	42.45	0.195	0.839
19	115	4.07	<	4.296	0.226	0.783	6.96	40.33	0.243	0.748
20	1103	3.455	<	4.11	0.655	1.284	9.79	42.76	0.477	1.008
Total	4,410	5.482		5.664	0.182	0.614	3.56	24.93	0.128	0.509

Table 5. Summary of Receiver Mistake Size by Secret Number and Sender Choice of Complexity (Main Sessions)

	All receiver decisions Mean values of receiver mistake size (|guess-truth|)			Conditional on receiver decision before time limit Mean values of receiver mistake size (|guess-truth|)		
Secret number	Low complexity (1–5)	Medium complexity (6–14)	High complexity (15–20)	Low complexity (1–5)	Medium complexity (6–14)	High complexity (15–20)
1	$\boxed{0.6}$	0.386	1.437	0.6	0.386	1.126
2	0.216	0.795	1.234	0.216	0.795	0.873
3	0.273	0.144	0.846	0.273	0.124	0.691
4	0.198	0.376	0.961	0.198	0.35	0.839
5	0.181	0.426	1	0.162	0.372	0.88
6	0.204	0.432	0.896	0.19	0.392	0.74
7	0.142	0.366	1.321	0.138	0.33	1.18
8	0.228	0.672	0.033	0.228	0.548	0.93
9	0.23	0.641	1.404	0.222	0.603	1.098
10	0.239	0.776	1.357	0.239	0.776	1.077
Total	0.225	0.469	1.133	0.221	0.434	0.91

4.1.2. Payoff Losses.

So far, we have documented that sender choices of complexity deviate from **the unraveling prediction** and that receiver guesses deviate from the true state. But do these deviations lead to payoff losses?
To address this possibility, we measure how far a subject is from taking the payoff-maximizing action in each decision problem, which provides a rough sense of the size and consequences of the “mistakes” they are making.
To do this, we construct the average opponent strategy from our data, determine the expected payoffs from taking each possible action, and then calculate how far the expected payoff for the taken action is from the highest expected payoff.
For senders, the possible actions are grouped as low (1–5), medium (6–14), and high (15–20) complexity.
For receivers, the possible actions are limited to the guesses available to them, which are integers between 1 and 10.

Table 6. Departure from Highest Expected Payoff (Main Sessions)

Panel A: Senders		
Secret number	Fraction of payoff loss from highest expected payoff given empirical distribution of opponent behavior	Fraction of payoff loss from payoff in the unraveling equilibrium
1[a]	0.516	
2	0.320	−0.714
3	0.152	−0.160
4	0.110	−0.043
5	0.103	−0.016
6	0.073	0.006
7	0.077	0.028
8	0.078	0.039
9	0.059	0.041
10	0.038	0.039
Total	0.153	−0.088

Panel B: Receivers		
Complexity	Fraction of payoff loss from highest expected payoff given empirical distribution of opponent behavior	Fraction of payoff loss from payoff in the unraveling equilibrium
Low (1–5)	0.138	0.299
Medium (6–14)	0.160	0.330
High (15–20)	0.167	0.311
Total	0.153	0.308

30%~33%

[a]In the unraveling equilibrium, senders with a secret number of one earn the minimum possible payoff. After normalizing this payoff to zero, it is not possible to calculate the fraction of payoff loss from zero.

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4.1.3. Evidence of Learning.

Table 7. Summary of Dynamics (Main Sessions)

Panel A

Secret number	Sender choice of complexity Mean Rounds 1–10	Rounds 11–20	Rounds 21–30	Fraction of sender payoff loss from highest expected payoff Mean Rounds 1–10	Rounds 11–20	Rounds 21–30
1	14.454	16.461	16.032	0.551	0.515	0.484
2	15.357	15.993	15.958	0.311	0.322	0.326
3	13.264	15.026	13.693	0.159	0.146	0.150
4	12.673	12.679	10.467	0.107	0.125	0.097
5	11.669	9.878	10.13	0.105	0.105	0.098
6	9.526	7.646	7.545	0.068	0.084	0.066
7	9.475	5.719	5.036	0.091	0.079	0.061
8	6.764	5.218	3.693	0.086	0.081	0.064
9	6.326	5.455	3.093	0.058	0.068	0.050
10	5.829	3.5	2.512	0.053	0.031	0.031
Total	10.624	9.786	8.774	0.159	0.156	0.142

Panel B

Complexity	Receiver mistake size (|guess-truth|) Mean Rounds 1–10	Rounds 11–20	Rounds 21–30	Conditional on before time limit Mean Rounds 1–10	Rounds 11–20	Rounds 21–30
Low (1–5)	0.254	0.206	0.222	0.247	0.202	0.219
Medium (6–14)	0.472	0.518	0.410	0.442	0.476	0.375
High (15–20)	1.274	1.099	1.004	1.015	0.947	0.751
Total	0.719	0.604	0.520	0.585	0.526	0.418

Panel C

Complexity	Fraction of receiver payoff loss from highest expected payoff Mean Rounds 1–10	Rounds 11–20	Rounds 21–30	Conditional on before time limit Mean Rounds 1–10	Rounds 11–20	Rounds 21–30
Low (1–5)	0.153	0.126	0.137	0.153	0.126	0.137
Medium (6–14)	0.182	0.148	0.138	0.181	0.148	0.136
High (15–20)	0.189	0.161	0.147	0.183	0.155	0.130
Total	0.174	0.143	0.141	0.171	0.141	0.135

图1 （A） （B）

4.1.4. Regression Results.

Table 8. Regressions of Sender Behavior (Main Sessions)

	Dependent variable Complexity		Dependent variable Payoff departure from the highest	
Secret number = 2	0.147	−0.252	−0.197***	−0.199***
	(0.423)	(0.418)	(0.0609)	(0.0625)
Secret number = 3	−1.467***	−1.297**	−0.361***	−0.360***
	(0.476)	(0.559)	(0.0714)	(0.0736)
Secret number = 4	−1.630**	−1.894**	−0.418***	−0.421***
	(0.749)	(0.711)	(0.0551)	(0.0567)
Secret number = 5	−2.884***	−3.358***	−0.426***	−0.429***
	(0.689)	(0.610)	(0.0533)	(0.0545)
Secret number = 6	−5.226***	−5.405***	−0.452***	−0.454***
	(0.753)	(0.633)	(0.0504)	(0.0512)
Secret number = 7	−5.485***	−5.742***	−0.433***	−0.436***
	(1.019)	(0.994)	(0.0501)	(0.0512)
Secret number = 8	−7.134***	−7.393***	−0.438***	−0.435***
	(0.886)	(0.858)	(0.0533)	(0.0543)
Secret number = 9	−7.363***	−7.614***	−0.453***	−0.453***
	(0.952)	(0.937)	(0.0487)	(0.0496)
Secret number = 10	−8.386***	−8.278***	−0.476***	−0.479***
	(0.842)	(0.928)	(0.0519)	(0.0529)
First five rounds	−0.298	−0.387	0.00783	0.00683
	(0.297)	(0.267)	(0.0116)	(0.0116)
Round 1-30	0.0427*	0.0409	−0.000657	−0.000601
	(0.0241)	(0.0249)	(0.00117)	(0.00114)
Round * (4 ≦ secret number ≦ 6)	−0.139***	−0.130***	0.000730	0.000685
	(0.0262)	(0.0212)	(0.00117)	(0.00109)
Round * (7 ≦ secret number ≦ 10)	−0.216***	−0.219***	−0.000183	−0.000298
	(0.0281)	(0.0301)	(0.00118)	(0.00114)
Individual demographics	Yes	No	Yes	No
Individual fixed effects	No	Yes	No	Yes
Observations	4,410	4,410	4,399	4,399
R^2	0.350	0.529	0.381	0.438

Notes. In parentheses are robust standard errors clustered by session. In Session 34, receivers' actual play is such that the highest payoff for draw = 1 is zero after our normalization, so we cannot calculate a fraction of payoff departure from zero. That is why columns (3) and (4) have 11 fewer observations. Regressions without individual fixed effects include dummies indicating whether demographics are missing and session fixed effects. Sample includes all sessions with complete demographic information.

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 9. Regressions of Receiver Behavior (Main Sessions)

	Dependent variable Receiver mistake size (| guess-truth |)		Dependent variable Payoff departure from the highest expected payoff	
Sender choice of complexity = 2	−0.0191	0.0228	−0.0229*	−0.0126
	(0.0590)	(0.0627)	(0.0121)	(0.0125)
Sender choice of complexity = 3	−0.162*	−0.0517	−0.0177	−0.0151
	(0.0849)	(0.0651)	(0.0152)	(0.0169)
Sender choice of complexity = 4	−0.199**	−0.130	0.000650	0.00884
	(0.0860)	(0.0784)	(0.0206)	(0.0212)
Sender choice of complexity = 5	−0.185**	−0.169**	0.0168	0.0213
	(0.0777)	(0.0793)	(0.0160)	(0.0172)
Sender choice of complexity = 6	−0.143	−0.111	0.00231	0.00419
	(0.116)	(0.0862)	(0.0216)	(0.0193)
Sender choice of complexity = 7	−0.286**	−0.0927	0.00188	0.0110
	(0.109)	(0.113)	(0.0201)	(0.0231)
Sender choice of complexity = 8	−0.0171	−0.0480	0.0127	0.0147
	(0.126)	(0.123)	(0.0192)	(0.0209)
Sender choice of complexity = 9	−0.0755	−0.143	0.0483*	0.0440
	(0.141)	(0.149)	(0.0258)	(0.0294)
Sender choice of complexity = 10	0.00256	0.000952	0.0343*	0.0442**
	(0.109)	(0.0981)	(0.0178)	(0.0198)
Sender choice of complexity = 11	0.0232	−0.0690	−0.0156	−0.00468
	(0.238)	(0.260)	(0.0295)	(0.0288)
Sender choice of complexity = 12	0.334	0.344	0.0118	0.0214
	(0.199)	(0.209)	(0.0204)	(0.0256)
Sender choice of complexity = 13	0.319	0.451	0.0559**	0.0608*
	(0.271)	(0.278)	(0.0259)	(0.0303)
Sender choice of complexity = 14	0.319	0.379	0.0776**	0.0870**
	(0.315)	(0.308)	(0.0305)	(0.0359)
Sender choice of complexity = 15	0.341*	0.475**	0.0212	0.0386*
	(0.193)	(0.226)	(0.0186)	(0.0221)
Sender choice of complexity = 16	0.0371	0.115	−0.0173	0.00332
	(0.194)	(0.209)	(0.0254)	(0.0270)
Sender choice of complexity = 17	0.391	0.570**	0.0679**	0.0755*
	(0.240)	(0.257)	(0.0324)	(0.0379)
Sender choice of complexity = 18	0.373	0.408*	0.0187	0.0145
	(0.239)	(0.238)	(0.0338)	(0.0358)
Sender choice of complexity = 19	0.317	0.274	0.0253	0.0438
	(0.258)	(0.250)	(0.0314)	(0.0332)
Sender choice of complexity = 20	0.587***	0.605***	0.0197	0.0315
	(0.181)	(0.197)	(0.0188)	(0.0226)
First five rounds	−0.0342	−0.0710	0.0127	0.0118
	(0.0614)	(0.0615)	(0.0106)	(0.0109)
Round	−0.00335	−0.00115	−0.000374	−0.000328
	(0.00349)	(0.00291)	(0.000527)	(0.000534)
Round * Medium complexity (6–14)	−0.00372	−0.00748	−0.00138*	−0.00145*
	(0.00628)	(0.00463)	(0.000752)	(0.000766)
Round * High complexity (15–20)	−0.00705	−0.0149***	−0.00151*	−0.00198**
	(0.00480)	(0.00459)	(0.000789)	(0.000859)
Response time (in seconds)	0.00824*	0.0114***	0.000482*	0.000397
	(0.00411)	(0.00376)	(0.000281)	(0.000333)
Individual demographics	No	No	No	No
Individual fixed effects	No	No	No	No
Observations	4,253	4,253	4,253	4,253
R^2	0.094	0.279	0.040	0.127

Notes. All regressions are conditional on receivers making a guess within the 60-second time limit. In parentheses are robust standard errors clustered by session. Regressions without individual fixed effects include dummies indicating whether demographics are missing and session fixed effects.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4.2. Reasons Behind Sender Mistakes

The largest sender losses come from two types of mistakes:

using high complexity when the state is high

Spite could drive senders to use high complexity when it is not justified in their own payoff.

using low complexity when the state is low.

If some subjects think that the socially correct action is to disclose simply for even low states, then they might act in this way and reward senders who do the same.

4.3. Reasons Behind Receiver Mistakes

- 4.3. Reasons Behind Receiver Mistakes
  - 4.3.1. Beliefs About Senders and Math Ability.
  - 4.3.2. Regressions of Receiver Mistakes on Beliefs.
  - 4.3.3. Structural Model.
  - 4.3.4. Estimating Math Errors.
  - 4.3.5. Estimating Strategic Confusion and Social Preferences.
  - 4.3.6. Baseline Predictions.
  - 4.3.7. Behavioral Factors: Naivete and Overconfidence.
  - 4.3.9. Overconfidence and Beliefs.

The two primary forces we consider for receiver over-guessing of complexity reports are **naivete** and **overconfidence about ability**, but we also consider several other possibilities, such as pure boundary effects, social preferences, confusion, and risk preferences.

Table 11. Summary of Structural Estimation of Receiver Guesses of High Complexity Reports Before Time Limit (Main Sessions)

Variable	Actual	Logit	Baseline	Social preferences	Risk aversion	Naivete	Over-confidence	Over-confidence + naivete	Over-weighting
Mean log-likelihood		−1.733	−1.553	−1.547	−1.553	−1.519	−1.272	−1.274	−1.261
Total log-likelihood		−2641	−2366	−2357	−2366	−2316	−1939	−1941	−1921
Parameter (lower)		0.047			0.010				16.760
Standard error		0.066			0.206				0.347
Parameter (upper)					0.135				23.076
Standard error					0.196				1.500
Secret number					Receiver bias (guess-truth) Mean values				
1–3	0.772	0.707	0.712	0.792	0.712	0.733	0.749	0.761	0.776
4–7	0.096	0.038	−0.181	−0.130	−0.181	−0.146	0.018	0.027	0.050
8–10	−0.891	−0.641	−1.662	−1.640	−1.662	−1.554	−0.904	−0.890	−0.800
Average distance		0.125	0.369	0.332	0.369	0.315	0.038	0.027	0.142
Secret number					Receiver bias (guess-truth) Mean values				
1	1.126	1.100	0.983	1.069	0.983	1.005	1.001	1.018	1.034
2	0.711	0.632	0.706	0.790	0.706	0.726	0.735	0.744	0.742
3	0.431	0.335	0.407	0.476	0.407	0.428	0.475	0.485	0.517
4	0.249	0.154	0.193	0.258	0.193	0.214	0.271	0.281	0.289
5	0.222	0.044	−0.082	−0.033	−0.082	−0.059	0.033	0.039	0.068
6	0.040	−0.044	−0.287	−0.255	−0.287	−0.262	−0.141	−0.133	−0.103
7	−0.462	−0.154	−1.172	−1.128	−1.172	−1.067	−0.432	−0.421	−0.385
8	−0.684	−0.335	−1.368	−1.341	−1.368	−1.264	−0.636	−0.625	−0.548
9	−0.980	−0.632	−1.725	−1.699	−1.725	−1.614	−0.926	−0.911	−0.840
10	−1.077	−1.100	−2.009	−1.999	−2.009	−1.898	−1.268	−1.250	−1.115
Average distance		0.159	0.393	0.370	0.393	0.340	0.091	0.093	0.936

Logit究竟是个啥？——离散选择模型之三 - 知乎 (zhihu.com)

4.3.1. Beliefs About Senders and Math Ability.

As mentioned previously, after all 30 rounds of the game were completed, we asked subjects to report what they think the secret number was on average in their session when the report complexity was 1–5, 6–10, 11–15, and 16–20.

We refer to a subject’s guess of the average secret number when the report complexity was 16–20 as their “complex guess,” and we classify subjects as being “naive” **if their complex guess is higher than the actual average secret number** when complexity was 16–20 in their session.

Across all 294 subjects, 12.6% are classified as naive. When naive, the average amount of naivete is 3.491, which is 98.9% above the actual average secret number in their session.

	样本量	回合结束后猜测均值	实际秘密数字均值
	294	2.471	3.636
16-20	294*12.6%	3.491	3.491/（1+98.9%）

Figure 2. (Color online) Average Secret Number and Stated Beliefs of Average Secret Number by Complexity of 1–5, 6–10, 11–15, or 16–20 with 95% Confidence Intervals (Main Sessions)

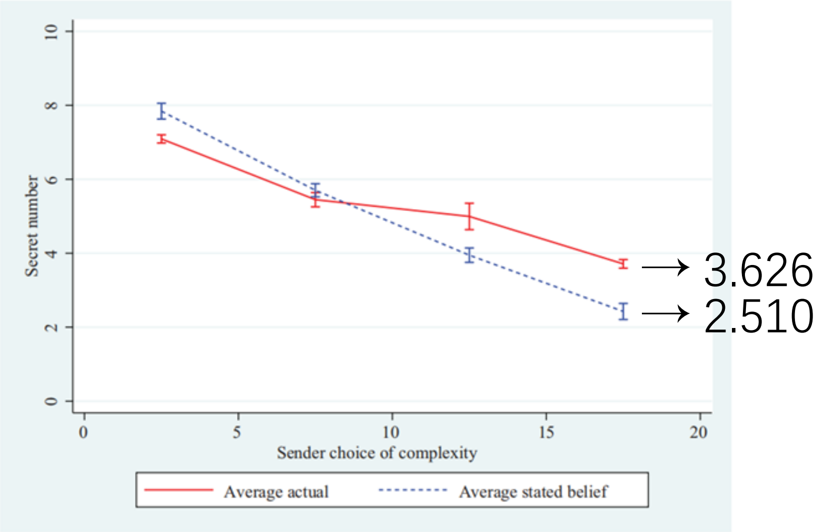


Figure 3. (Color online) Average Sender Choice of Complexity and Stated Beliefs of Average Sender Choice of Complexity by Secret Number with 95% Confidence Intervals (Main Sessions)

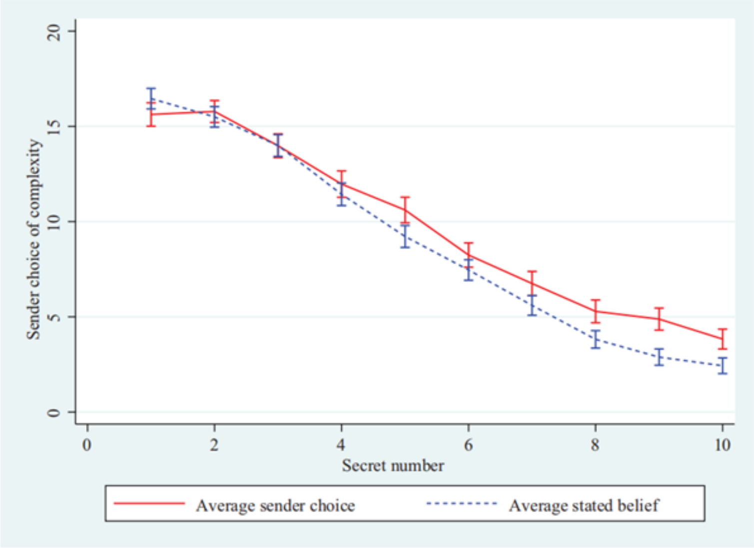


Table 10. Summary of Receiver Guess and Stated Beliefs (Main Sessions)

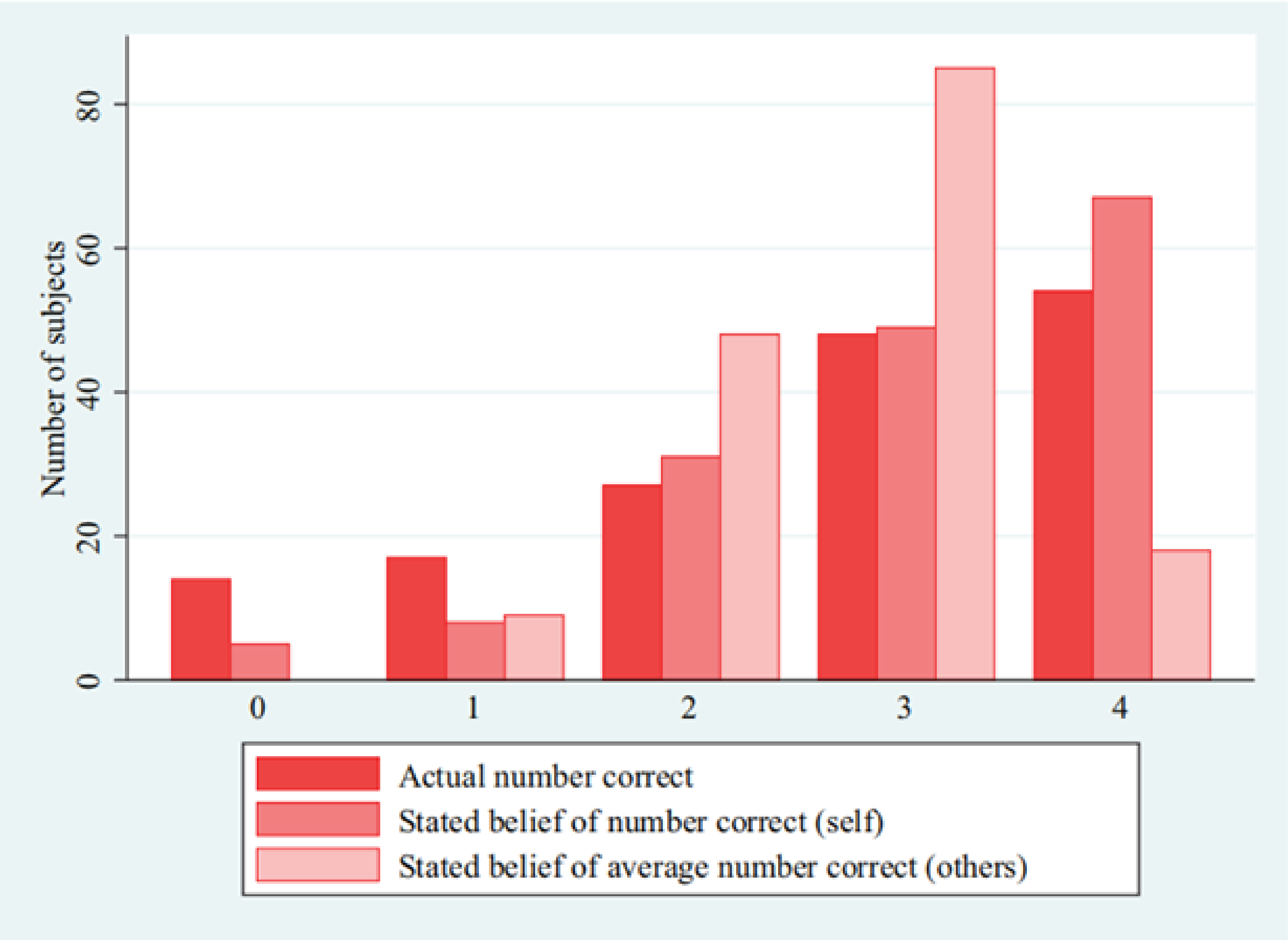
Panel A: Complex guess (stated belief of average secret number for a given complexity)						
	All received decisions			Conditional on before time limit		
	Secret number	Receiver guess	Complex guess	Secret number	Receiver guess	Complex guess
Complexity	Mean	Mean	Mean	Mean	Mean	Mean
1–5	7.091	7.064	7.813	7.091	7.064	7.823
6–10	5.448	5.396	5.756	5.447	5.404	5.756
11–15	4.701	4.835	3.867	4.655	4.818	3.848
16–20	3.626	4.191	2.51	3.636	4.055	2.471
Panel B: Inferred guess (secret number inferred from stated beliefs of sender choices)						
	All receiver decisions			Conditional on before time limit		
	Secret number	Receiver guess	Inferred guess	Secret number	Receiver guess	Inferred guess
Complexity	Mean	Mean	Mean	Mean	Mean	Mean
Low (1–5)	7.091	7.064	7.845	7.091	7.064	7.849
Medium (6–14)	5.338	5.344	4.893	5.326	5.354	4.891
High (15–20)	3.712	4.222	2.546	3.72	4.097	2.526

Note. Out of all receiver decisions, 6.8% have a missing value for inferred guess because those subjects indicate that senders will never choose some complexity level.

答题情况	人数	真实情况	自己猜测
全对	54	33.75%	41.88%
错1个	48	30%	72.5%-41.88%
错2个	27	16.88%	
错3个		10.62%	
全错		8.75%	

实际答题正确数均值	2.694
至少错一个的受试者预测	2.694

Figure 4. (Color online) Math Test Performance and Stated Beliefs of Math Test Performance



4.3.2. Regressions of Receiver Mistakes on Beliefs.

Table 12. Regressions of Receiver Over-Guessing in Complex Rounds if Completed Math Test (Main Sessions)

	Dependent variable: Receiver mistake (guess-truth)		Dependent variable: Receiver mistake size (|guess-truth|)	
Sender choice of complexity = 15	−0.274*	−0.233	−0.0920	−0.0559
	(0.143)	(0.178)	(0.175)	(0.221)
Sender choice of complexity = 16	0.223	0.243	−0.212	−0.0716
	(0.248)	(0.325)	(0.268)	(0.376)
Sender choice of complexity = 17	−0.473*	−0.481	−0.113	−0.155
	(0.266)	(0.365)	(0.112)	(0.128)
Sender choice of complexity = 18	−0.297	−0.647**	−0.294	−0.338
	(0.233)	(0.298)	(0.193)	(0.288)
Sender choice of complexity = 19	−0.558	−0.356	−0.239	−0.121
	(0.320)	(0.399)	(0.295)	(0.382)
First five rounds	−0.313	−0.211	−0.283	−0.247
	(0.184)	(0.187)	(0.173)	(0.205)
Round	−0.00277	−0.00125	−0.0149*	−0.0207**
	(0.00711)	(0.00909)	(0.00722)	(0.00898)
Size of naivete (complex guest-actual average if > 0)	0.245**		0.233	
	(0.0829)		(0.139)	
Size of overconfidence (guess correct - actual correct if > 0)	0.236**		0.295*	
	(0.108)		(0.144)	
Individual demographics	No	No	No	No
Individual fixed effects	No	No	No	No
Observations	813	813	813	813
R^2	0.085	0.270	0.085	0.359

Notes. All regressions are conditional on receivers making a guess within the 60-second time limit. In parentheses are robust standard errors clustered by session. Regressions without individual fixed effects include dummies indicating whether demographics are missing and session fixed effects.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

4.3.3. Structural Model.

In the model, we assume that a receiver facing a complex message (**c ≥ 15**) has prior beliefs about the likelihood of each secret number **b** given by **F** (the distribution of sender types using this type of complexity).
The receiver then observes a noisy signal of the secret number, which can be interpreted as either an error in summing the numbers or partial attention to the grid of numbers. We assume that this noise signal is generated by adding to the secret number an error term e drawn from the distribution G (for this complexity level), so that

$$x = b + e, \text{ where } e \sim G:$$

We assume that the distribution of additive errors **G** has support over the integers {−9, −8, ⋯, 0, ⋯, 8, 9}. To increase power, we assume this distribution is symmetric, so the distribution has just 10 parameters to estimate. Based on the signal **x** and their prior beliefs **F**, the receiver forms posterior beliefs **γ** and takes an action **a** (makes the guess) that maximizes the expected utility subject to some probability of making strategic errors. This decision rule is given by the following optimization problem:

$$\max_{a\in A} \sum_{b\in B} \gamma(b|x) U_R(a,b),$$

$$\text{where } \gamma(b|x) = \frac{F(b)G(x-b)}{\Sigma_{b'\in B} F(b')G(x-b')}.$$

We also assume that strategic confusion results in a receiver sometimes guessing in a uniform random way. In **the level-k model**, this is often designated as the level-0 behavior. Because we are using a representative agent model, this is as if some fraction of agents are level-0 agents. Formally, this means, for some fraction of choices, the receiver chooses every action with equal probability.

As a robustness check, we assume that the receiver sometimes uses social preferences that take the form proposed by Fehr and Schmidt (1999). Note that only one parameter of this model (advantageous inequality **β**) has bite. For these choices, the decision rule is instead given by the following optimization problem:

$$\max_{a \in A} \sum_{b \in B} \gamma(b|x)[U_R(a,b) - \beta(U_R(a,b) - U_S(a,b))].$$

As an additional robustness check, we assume that utility takes the constant relative risk aversion form, which means that we allow a free parameter **α**. In this check, we assume that the utility of the receiver is instead given by

$$\frac{U_R(a,b)^{1-\alpha}}{1-\alpha}.$$

We also consider two possible behavioral factors: naivete and overconfidence. We add naivete to our model by assuming that, with some probability, receivers think that all states are equally likely. In the level-k approach, this often constitutes level-1 beliefs: that opponents are guessing randomly. Formally, this means that $\gamma(b|x) = \frac{1}{|A|}.$

We add overconfidence to our model by assuming that, with some probability, receivers think that noise is actually draw from the distribution G' when is actually drawn from G

4.3.4. Estimating Math Errors.

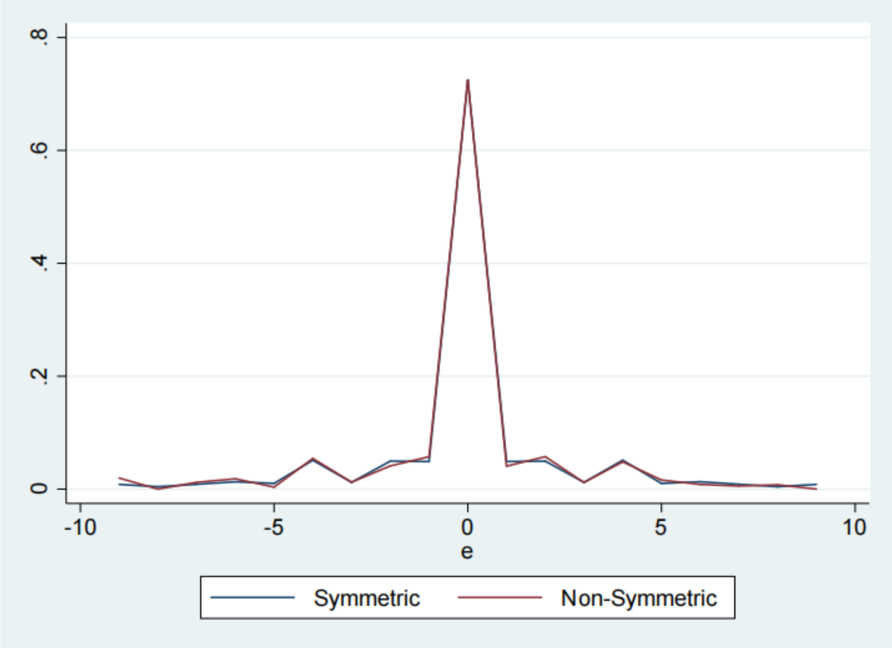
We assume that **math error** determines the precision of the signal **x** and, therefore, affects the receiver's posterior beliefs about the secret number.

We could impose strong assumptions on the distribution of math errors and try to identify it using receiver decisions in the game, but we choose instead to estimate it out of sample for cleaner identification.

By assuming that receivers guess their signal, we can identify from guesses and secret numbers the frequency with which each signal is realized. **To estimate G** in this way, we used the math test answers for the 160 subjects who completed the math test.

A.3 Non-parametric estimates of *G* and *G'*

Figure A1. Non-parametrically estimated distribution of additive error term (by whether assume that distribution is symmetric)



4.3.5. Estimating Strategic Confusion and Social Preferences.

We estimate the degree of strategic confusion and the social preferences of the subjects jointly, using the guesses of receivers when the message has been reported as low complexity ($c \leqslant 5$).

In practice, it is likely that social considerations when messages are complex are different from when messages are simple as receivers may feel some positive reciprocity when simple reports are made.

The parameters of this model were estimated using the Nelder–Mead method, and the standard errors were computed using 1,000 bootstrapping samples.

The estimates were a 7.4% probability of uniform random choice (with a standard error of 0.007), a 2.3% probability of using social preferences (with a standard error of 0.005), and a 0.658 advantageous inequality parameter (with a standard error of 0.194)

4.3.6. Baseline Predictions.

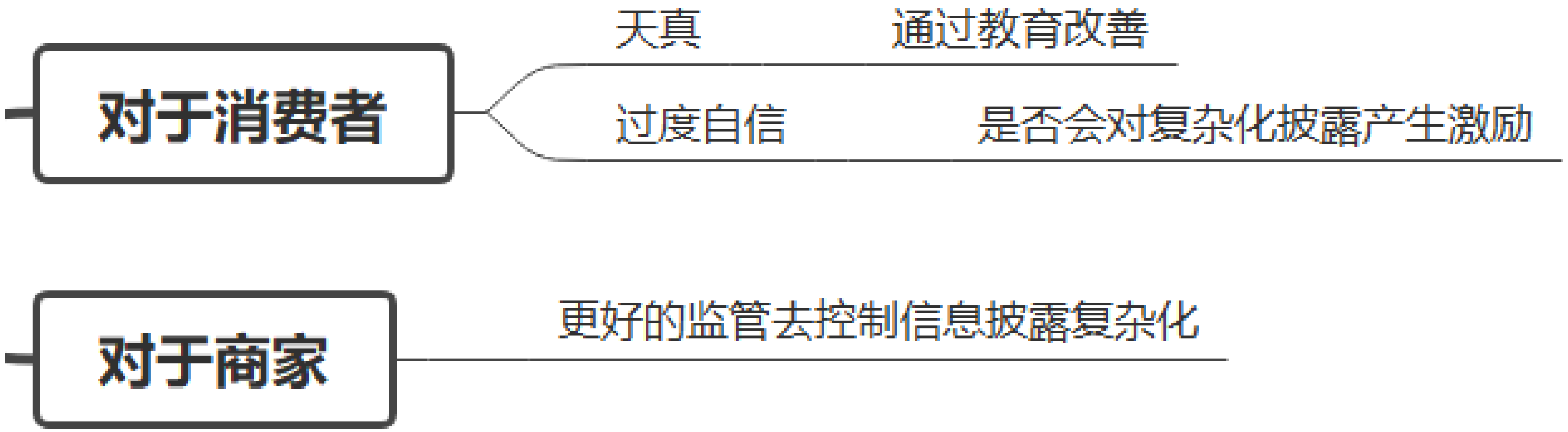
4.3.7. Behavioral Factors: Naivete and Overconfidence.

Table 11. Summary of Structural Estimation of Receiver Guesses of High Complexity Reports Before Time Limit (Main Sessions)

Variable	Actual	Logit	Baseline	Social preferences	Risk aversion	Naivete	Over-confidence	Over-confidence + naivete	Over-weighting
Mean log-likelihood		−1.733	−1.553	−1.547	−1.553	−1.519	−1.272	−1.274	−1.261
Total log-likelihood		−2641	−2366	−2357	−2366	−2316	−1939	−1941	−1921
Parameter (lower)		0.047			0.010				16.760
Standard error		0.066			0.206				0.347
Parameter (upper)					0.135				23.076
Standard error					0.196				1.500
					Receiver bias (guess-truth) Mean values				
Secret number									
1–3	0.772	0.707	0.712	0.792	0.712	0.733	0.749	0.761	0.776
4–7	0.096	0.038	−0.181	−0.130	−0.181	−0.146	0.018	0.027	0.050
8–10	−0.891	−0.641	−1.662	−1.640	−1.662	−1.554	−0.904	−0.890	−0.800
Average distance		0.125	0.369	0.332	0.369	0.315	0.038	0.027	0.142
					Receiver bias (guess-truth) Mean values				
Secret number									
1	1.126	1.100	0.983	1.069	0.983	1.005	1.001	1.018	1.034
2	0.711	0.632	0.706	0.790	0.706	0.726	0.735	0.744	0.742
3	0.431	0.335	0.407	0.476	0.407	0.428	0.475	0.485	0.517
4	0.249	0.154	0.193	0.258	0.193	0.214	0.271	0.281	0.289
5	0.222	0.044	−0.082	−0.033	−0.082	−0.059	0.033	0.039	0.068
6	0.040	−0.044	−0.287	−0.255	−0.287	−0.262	−0.141	−0.133	−0.103
7	−0.462	−0.154	−1.172	−1.128	−1.172	−1.067	−0.432	−0.421	−0.385
8	−0.684	−0.335	−1.368	−1.341	−1.368	−1.264	−0.636	−0.625	−0.548
9	−0.980	−0.632	−1.725	−1.699	−1.725	−1.614	−0.926	−0.911	−0.840
10	−1.077	−1.100	−2.009	−1.999	−2.009	−1.898	−1.268	−1.250	−1.115
Average distance		0.159	0.393	0.370	0.393	0.340	0.091	0.093	0.936

5. Conclusion and Policy Implications

研究结果突出了企业战略性地将向消费者披露的信息复杂化的动机，这可能会损害消费者，并削弱信息披露的有效性。



2. Literature Review

- 2.1. Voluntary and Mandatory Disclosure
- 2.2. Obfuscation and Behavioral Biases
- 2.3. Laboratory Experiments

Ginger Jin

University of Maryland, Department of Economics

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Lee J Styslinger III Associate Professor, Harvard Business School

Economics of Digitization Behavioral Economics

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More competitive search through regulation A Bonatti, LE Celis, GS Crawford, D Dinielli, P Heidhues, M Luca, T Salz, ... Policy Discussion Paper		2021
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