The disenchantment of social life

The transformation of trust in platform society

“All views and ideas expressed in this presentation are my own and do not represent my employer.”

Paolo Parigi, IRiSS, Stanford University & Staff Researcher @ META: Lecture at College Carlo Alberto, November 2025

"The times they are a-changin'" (Bob Dylan)

The disenchantment process

A growing number of interpersonal interactions are now mediated by tech platforms—whether I'm searching for a partner, a place to stay, someone to take care of my pets, algorithms and platforms stand between me and the other.

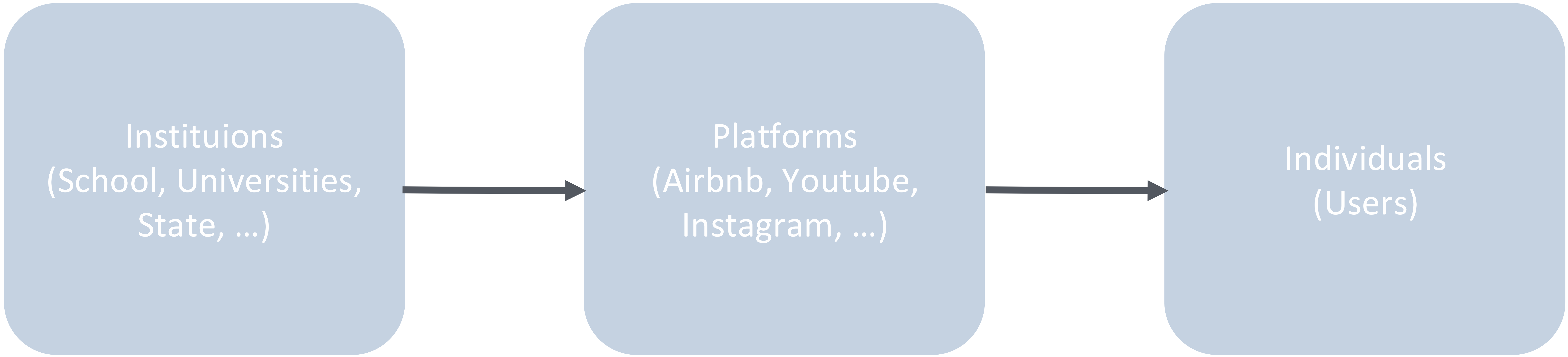
"The fate of our times is characterized by rationalization and intellectualization and, above all, by the disenchantment of the world." (Max Weber)

Platforms, not the institutions of the State (the bureaucracy, in Weberian language), are the private organizations quantifying the social world.

Platforms represent a new business model that extract data from individuals as raw material for more optimizations (Srinicek 2017) and (some think) surveillance (Zuboff 2019).

The Platform Society: New Architecture of Social Life

- Infrastructure of Interaction: Platforms mediate relationships once governed by communities, media, or the state (Snricek 2017. Van Dijck, Poell & Waal, 2018).
- Quantification of Social Life: Ratings, likes, and metrics become the new languages of credibility and trust.
- Private Governance: Platforms now set behavioral norms and rules — not through law, but through code and algorithms.



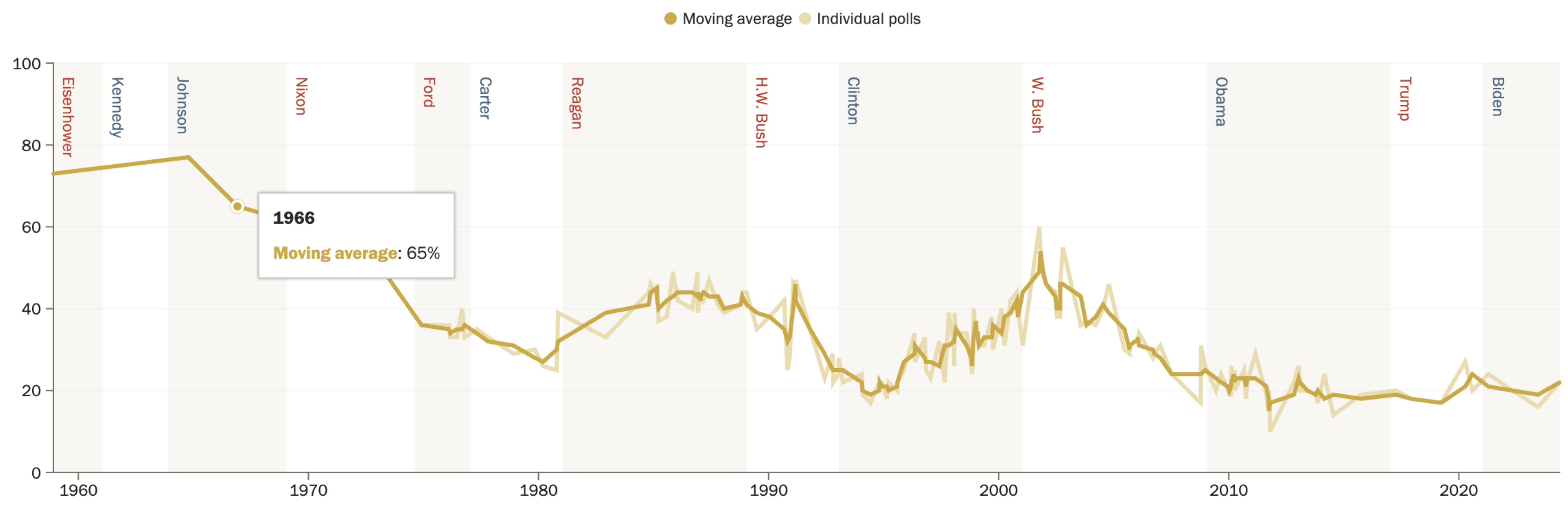
The “trust crisis”

Declining trends in trust all over the world

- In the US, interpersonal trust and trust in institutions are historically low (Pew research):
  - Only ~ 1 in 3 Americans say ‘most people can be trusted’ (34%)
  - Only ~ 1 in 5 say they trust the federal government to do the right thing (22%)

Public trust in government near historic lows

% who say they trust the government to do what is right just about always/most of the time



Sources: Pew Research Center, National Election Studies, Gallup, ABC/Washington Post, CBS/New York Times, and CNN surveys.

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How do we measure trust?

- Trust is treated as a stable individual attitude — measurable, comparable, and context-free.
- Questions for measuring trust (see box on the right) are standardized to make comparisons across contexts and countries possible.
- Trust is considered an attitude. It reflects internal state not behavior.
- These measures worked well when trust was anchored in stable institutions. But in an era of fluid affiliations and algorithmic mediation, they risk mistaking change for decline.

Some examples of how attitudes about trust are currently measured

From GSS-like instrument:

<u>Interpersonal trust</u>: *“Generally speaking, would you say that most people can be trusted, or that you can’t be too careful?”*

<u>Trust in institutions</u>: *“How much of the time do you trust the government to do what is right?”*

<u>From Gallup</u>: *“Now I am going to read you a list of institutions in American society. Please tell me how much confidence you, yourself, have in each one — a great deal, quite a lot, some, or very little?”*

When platforms mediate interactions, is the conceptualization of trust as an attitude still accurate to understand how people make choices?

Trust as a practice

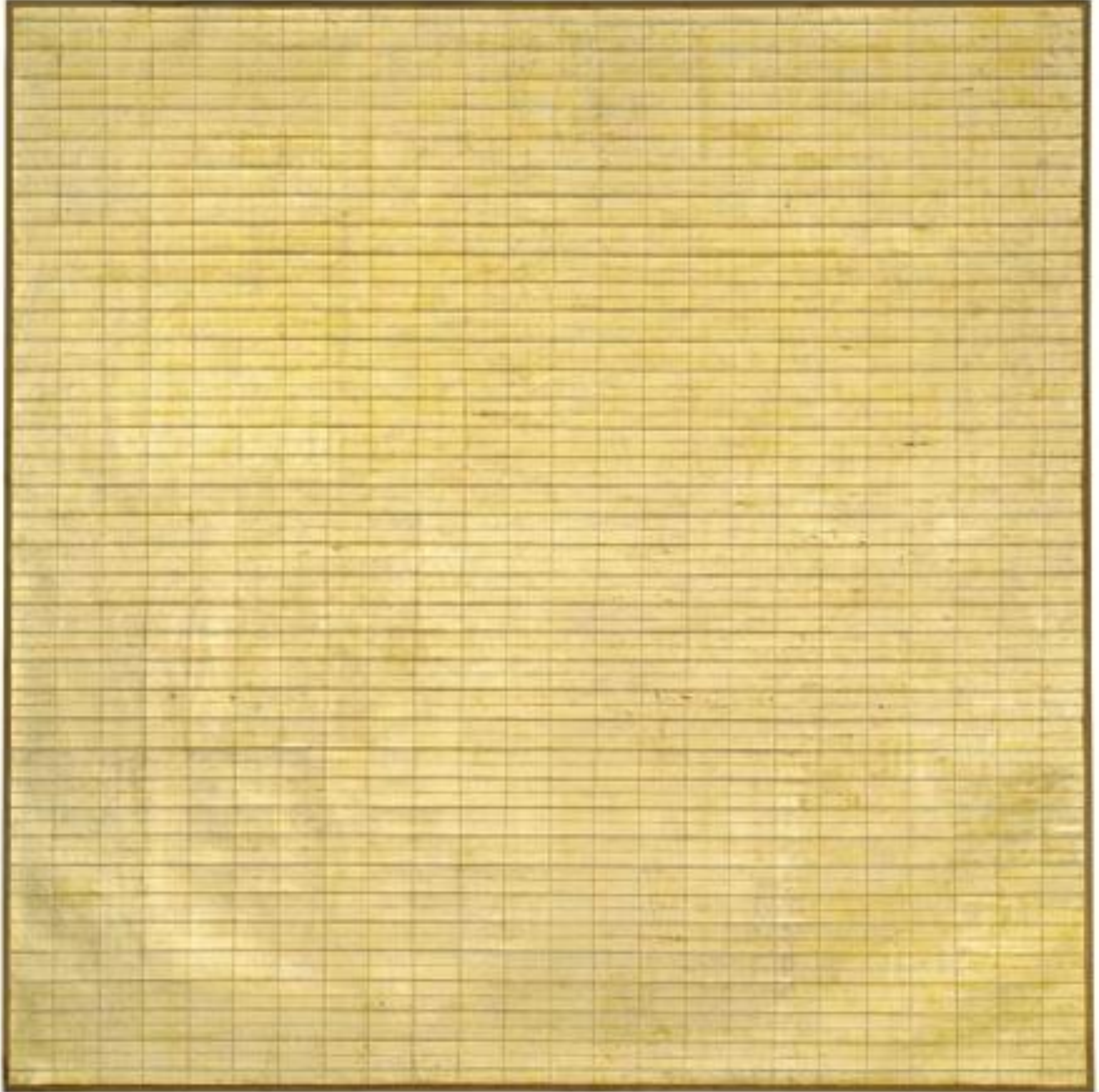
From what people think about trust to what they do to make it possible

When you book an Airbnb, you read reviews, scan photos, check host responses, and maybe exchange a few messages before committing.
→ This isn't "believing the host is good"; it's a procedural calibration of risk guided by cues from the platform (ratings, verifications, response rates).

"Trust is a skillful suspension of doubt, bracketing a stark contrast between knowing and not knowing, where intuition and experience come into play." (Gil Eyal et al, 2024)

Instead of treating trust as a static property that can be measured by close-format survey questions, in this lecture I think of "trusting" as a skillful act that is highly context-dependent.

Part of the trust crisis we are living through now is not a loss but a *shift* and we lack the instruments for measuring this shift.



What are the consequences for *how* we trust in the Platform society?

Related work

Abrahao, B., Parigi, P., Gupta, A., & Cook, K. S. (2017). "Reputation offsets trust judgments based on social biases among Airbnb users". *PNAS*, 114(37), 9830–9835.

Qiu, W., Parigi, P., & Abrahao, B. (2018). "More stars or more reviews? Differential effects of reputation on trust in the sharing economy." *Proceedings of CHI 2018*, 1–11.

Parigi, P., Santana, J. J., & Cook, K. S. (2017). "Online field experiments: Studying social interactions in context." *Social Psychology Quarterly*, 80(1), 5–27.

Santana, J. J., & Parigi, P. (2015). "Risk aversion and engagement in the sharing economy." *Games*, 6(4), 560–573.

Parigi, P., & Lainer-Vos, D. (2021). "Online reputation systems and the thinning of trust." *Yale Journal of Law & Technology*, 23.

Friendship, Agnes Martin. 1963

1. The thinning of trust

Trust becomes scalable

When we view trust as a practice, we see individuals engaging with the infrastructures that platforms create: ratings, reviews, verification badges, etc…

These practices are not beliefs ("I think you are trustworthy"); They are calibrated and contextualized processes for trusting a stranger or new information.

The more trust becomes a procedure that relies on platform infrastructure, the more it becomes quantifiable, *thinner,* i.e. domain specific and quantified (Parigi & Leirner-Vos 2023).

- Note the difference with Giddens "trust in abstract systems", as part of late modernity. Thin trust is very personal and tailored to the person deemed trustworthy. It is thin because it does not carry over different domains.

Platforms manage thin trust and make it scalable, making possible the emergence of new sectors such as the Sharing Economy.

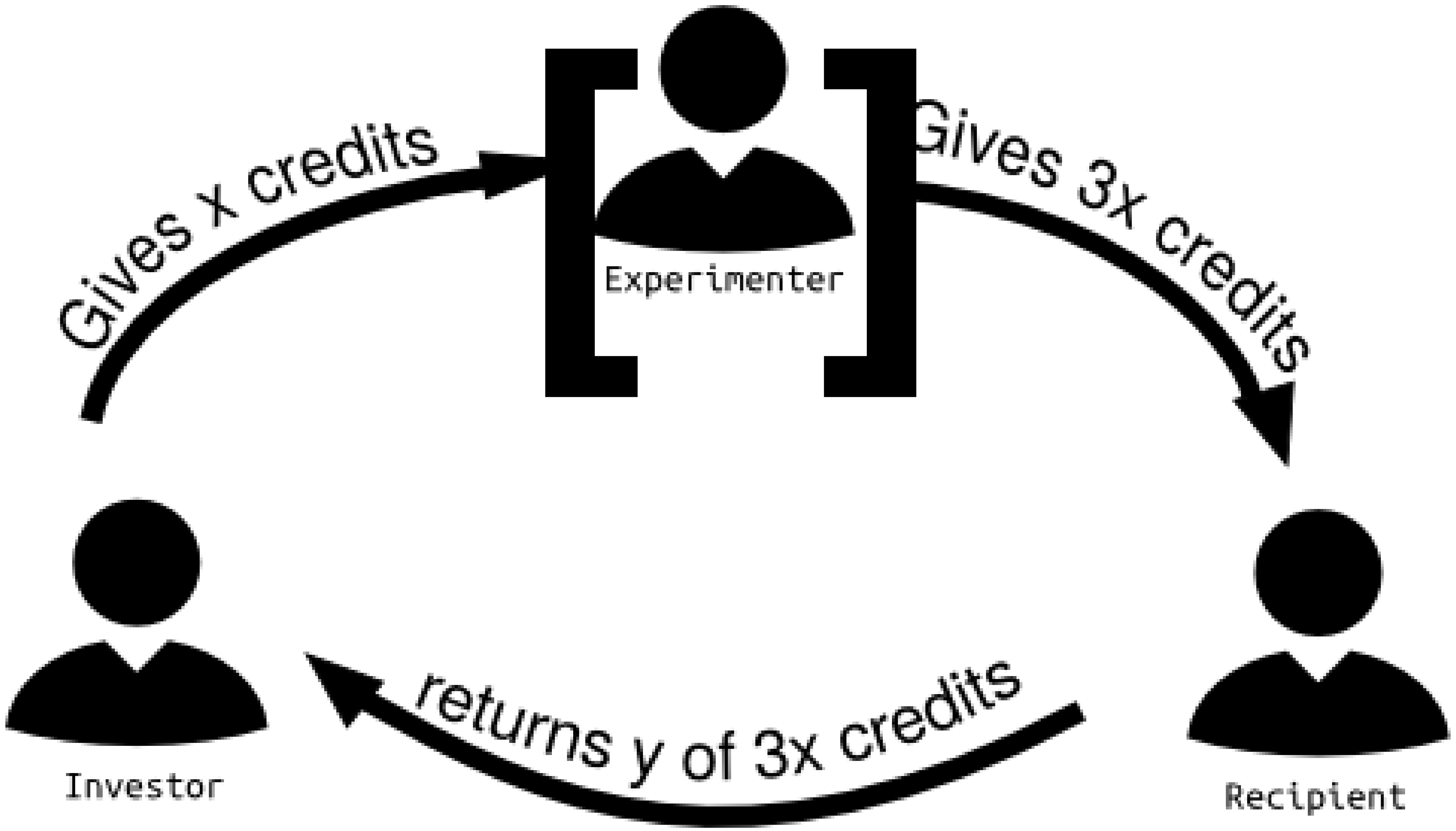
Stanford-Airbnb joint study

Work supported by NSF Grant# 1257138

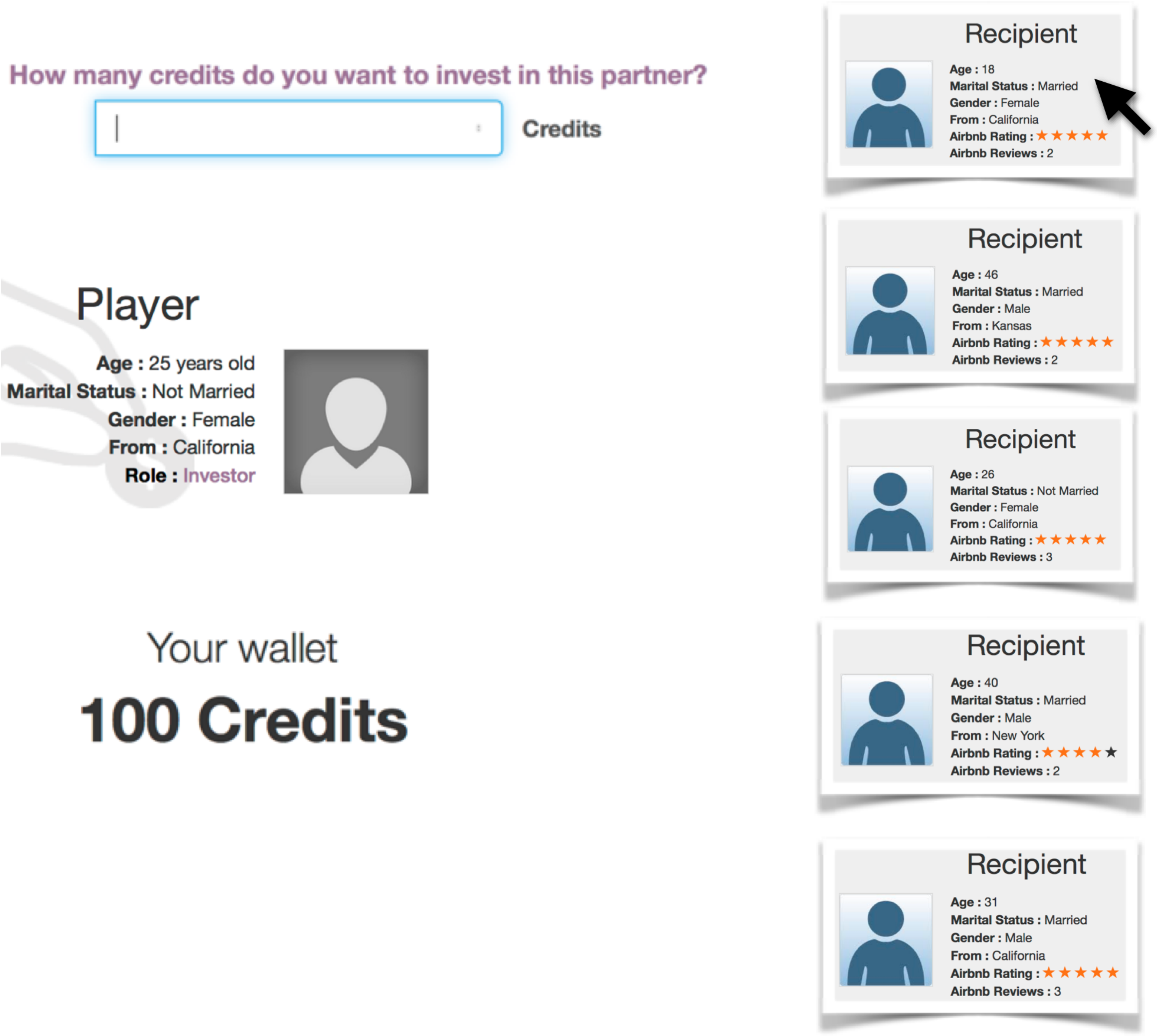
- 100K invitations to Airbnb users
    - 8,906 registered to participate
- Each participant plays an **investment game** with 5 other "Airbnb users"
- US$ 10,000 in prizes
    - 100 prizes of US$ 100 (chances of winning proportional to points)

Abrahao, B. Parigi, P. Gupta, A. K. Cook. 2017. "Reputation offsets trust judgments based on social biases among Airbnb users", PNAS 114 (37)

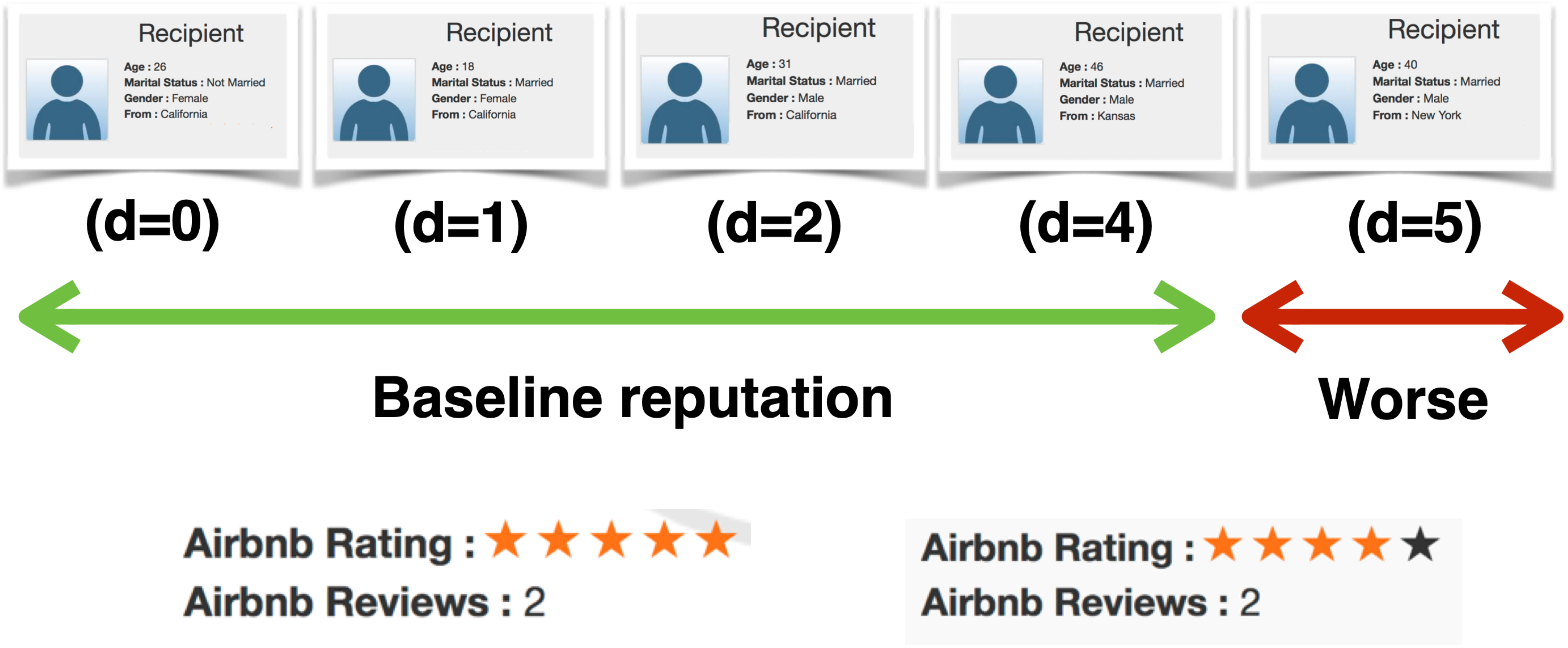
The investment game



Game screen

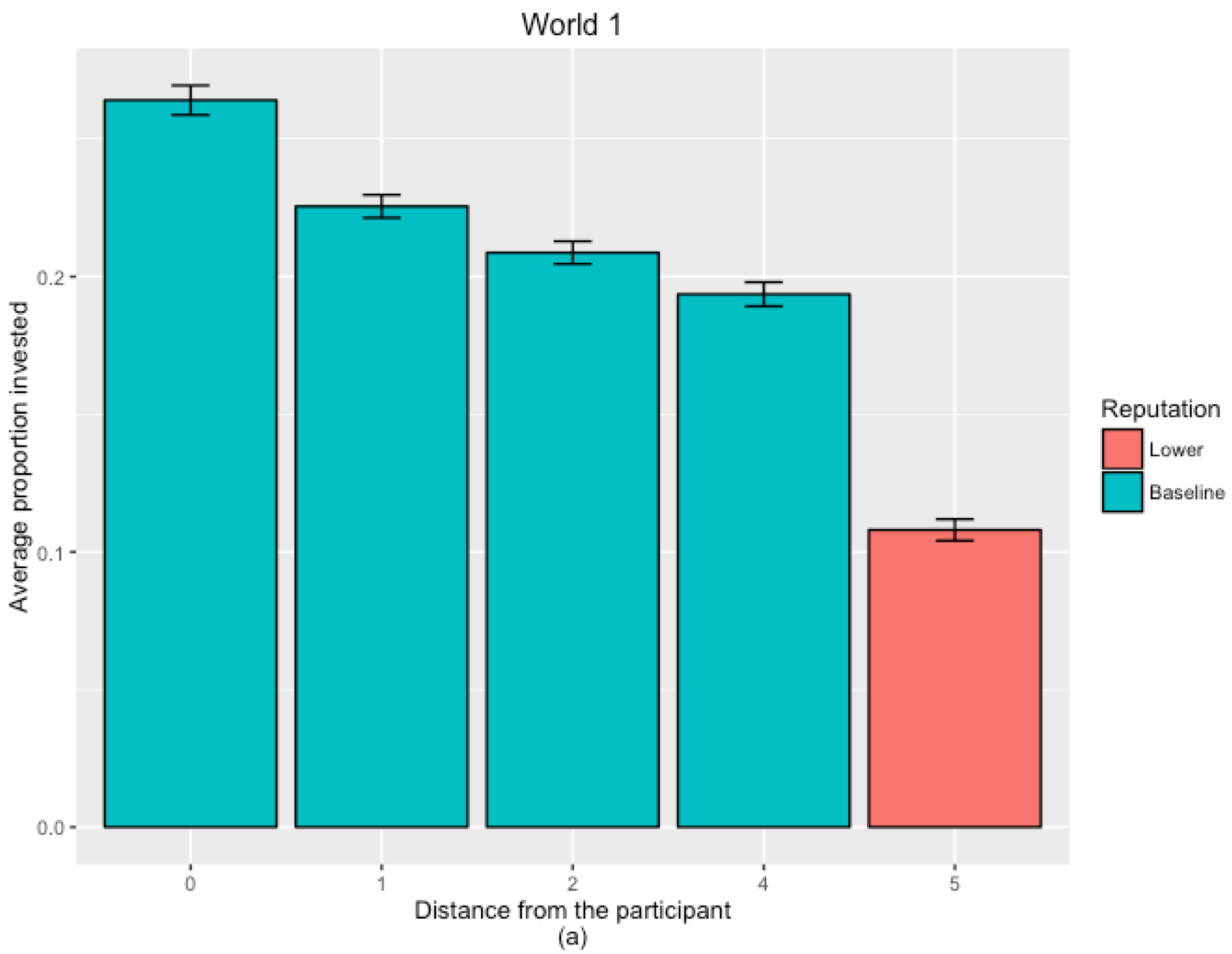

How many credits do you want to invest in this partner?
Credits
Player
Age : 25 years old
Marital Status : Not Married
Gender : Female
From : California
Role : Investor
Your wallet
100 Credits
Recipient
Age : 18
Marital Status : Married
Gender : Female
From : California
Airbnb Rating :
Airbnb Reviews : 2
Recipient
Age : 46
Marital Status : Married
Gender : Male
From : Kansas
Airbnb Rating :
Airbnb Reviews : 2
Recipient
Age : 26
Marital Status : Not Married
Gender : Female
From : California
Airbnb Rating :
Airbnb Reviews : 3
Recipient
Age : 40
Marital Status : Married
Gender : Male
From : New York
Airbnb Rating :
Airbnb Reviews : 2
Recipient
Age : 31
Marital Status : Married
Gender : Male
From : California
Airbnb Rating :
Airbnb Reviews : 3

Airbnb reputation



World 1

Investments in World 1



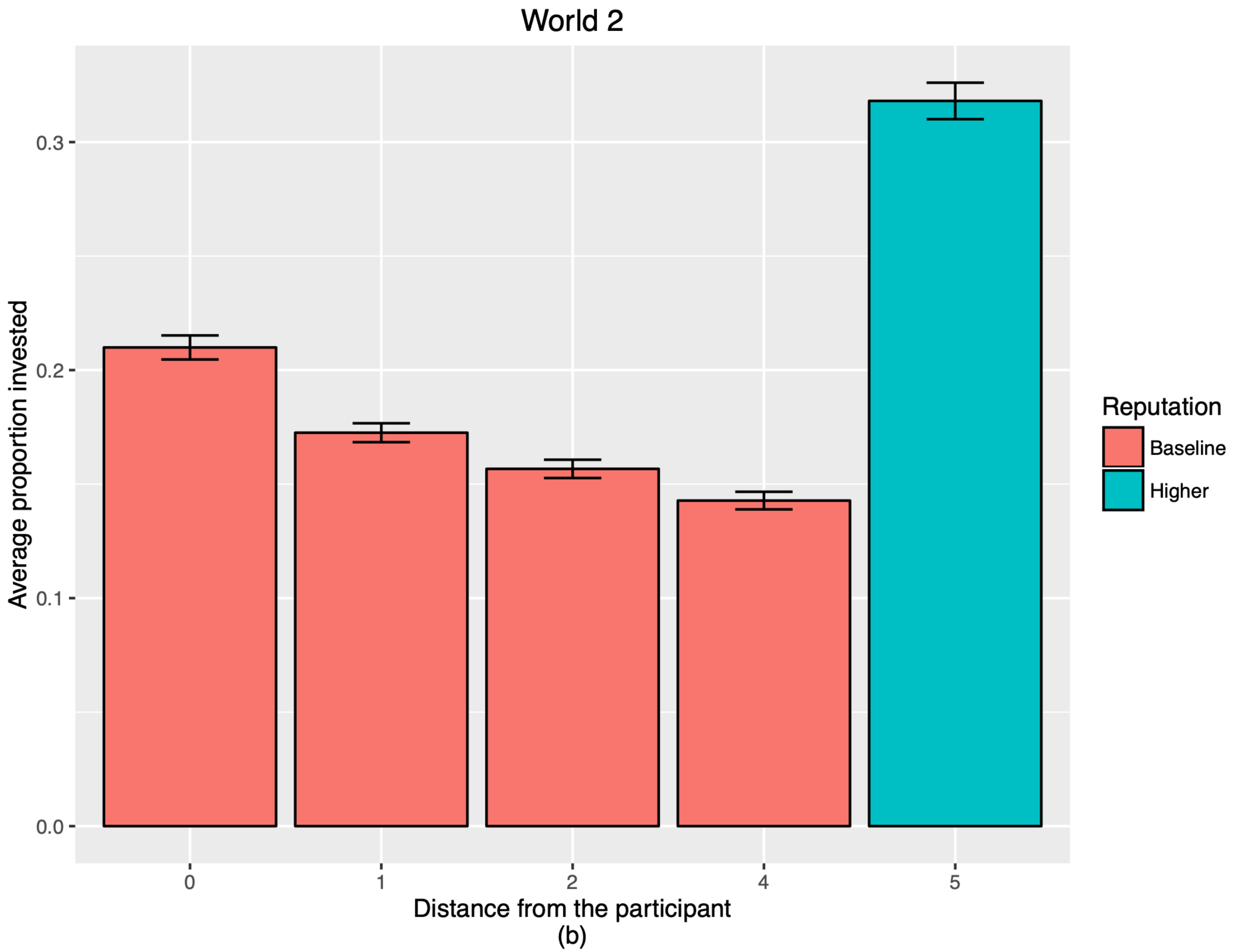
Airbnb reputation

Airbnb Rating : ★★★★★
Airbnb Reviews : 2

Airbnb Rating : ★★★★★
Airbnb Reviews : 26

World 2

Investments in World 2



Structural constraints of the research design

Profile Distance	0	1	2	4	5
Participant					
Age	**S**	**S**	**S**	**D***	**D***
Gender	**S**	$\mathbf{D_{R1}}$	**D**	**D**	**D**
Marital Status	**S**	**S**	$\mathbf{D_{R2}}$	**D**	**D**
Region	**S**	**S**	**S**	**D***	**D***
Rating	**B**	**B**	**B**	**B**	$\mathbf{D^{*}_{R3}}$
Reviews	**B**	**B**	**B**	**B**	**B**

R1: Gender, **R2**: Marital Status, **R3**: Rating, *Includes random choice of values

Fig. S2. Example of the structure of a user session. The symbol S in the figure indicates the same values as the participant's features; D indicates a different value, which increases distance in the social space; and B indicates baseline reputation. The random decision of which feature to vary to increase distance from $d = 0$ to $d = 1$ is labeled $R1$, and to $d = 2$, $R2$, and the reputation feature we vary, $R3$. Other random choices include the profiles' age and region (whenever they have to be different from those of the player) to values outside of the player's own age group and region.

Multilevel model with, (1) S (subject's demographics), (2) P (profile's characteristics), (3) P - S, cross-level interactions

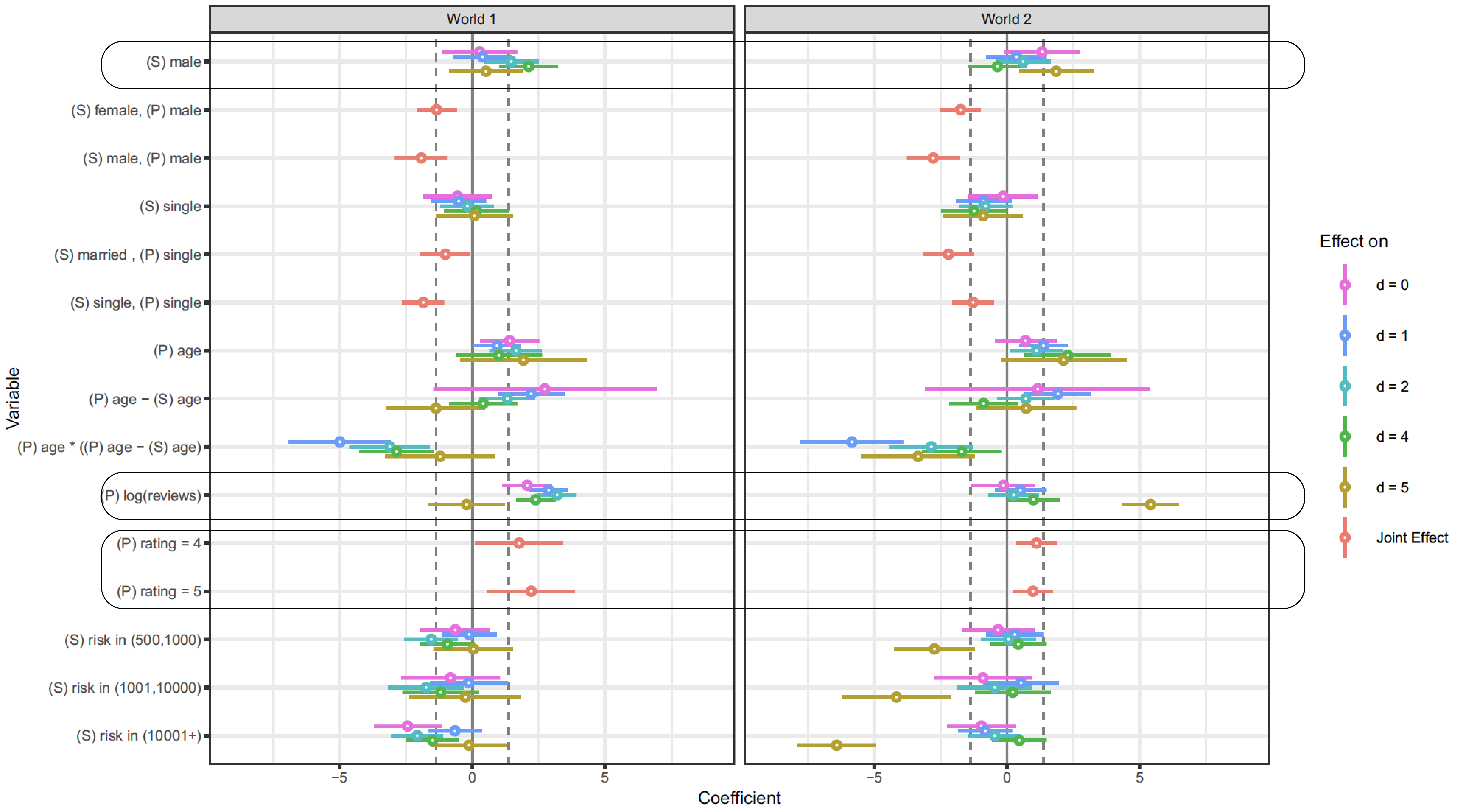


Fig. 2. The effects of the covariates associated with the participant (S) and profiles (P) in the multivariate multilevel model. The dashed lines have the values ±1.37, which correspond to the smallest average investment difference between two profiles with baseline reputation, minus two standard errors.

Real-world data validation: 1 million requests to stay

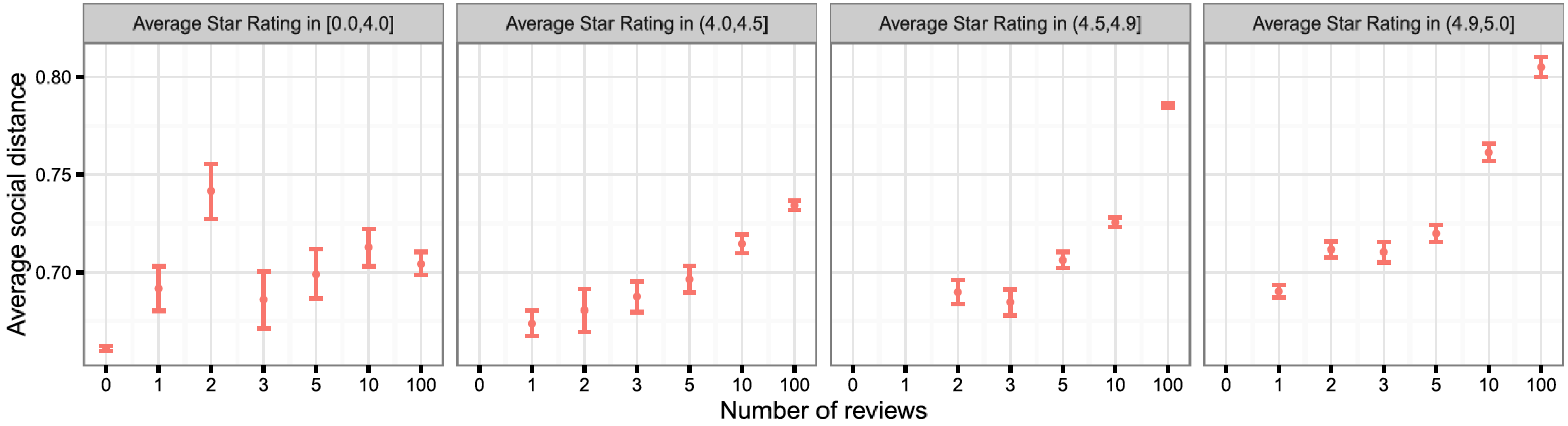


Fig. 3. Real-world data from Airbnb show that an increased reputation of the host in the form of rating (graph) and number of reviews (*x* axis) results in greater diversity of guests who selected them (*y* axis).

What are the Platforms teaching us?

Related work

Parigi, P., & Henson, W. (2014). Social isolation in America. Annual Review of Sociology, 40(1), 153–171.

Parigi, P., & State, B. (2014). Disenchanting the world: The impact of technology on relationships. In L. M. Aiello & D. McFarland (Eds.), Social Informatics (SocInfo 2014), Lecture Notes in Computer Science, Vol. 8851, pp. 166–182. Springer.

Parigi, P., State, B., Dakhlallah, D., Corten, R., & Cook, K. S. (2013). A community of strangers: The dis-embedding of social ties. PLOS ONE, 8(7), e67388.

Cook, K., & Parigi, P. (2024). Social Networks, Power and Dependence. In R. Light & J. Moody (Eds.), The Oxford Handbook of Social Networks. Oxford University Press. Forthcoming.

The Instagram Self, Amelia Ulman. 2016

2. We are all *users*

Platforms are a Technology of the Self

We all become *users* and the platforms teach us how to perform. Technologies like Zoom or Slack teach us how to collaborate, how to appear productive and trustworthy. They teach us how to monitor ourselves, to be constantly reachable and how to quantify our contributions.

Foucault: "*Technologies of the self permit individuals to effect by their own means, or with the help of others, a* ***certain number of operations on their own bodies and souls, thoughts, conduct, and way of being****, so as to transform themselves in order to attain a certain state of happiness, purity, wisdom, perfection, or immortality.*" (Technology of the Self, 1982)

As users we interiorize the requirements of the algorithms. For example, controversies drive engagements and politicians everywhere in the world make incendiary statements to be picked up by the algorithm and be always on top of the feed.

Learning how to trust

Platform(s) teach us how to perform trust

- What the results from the experiment show is not only that we need new way for measuring trust but also how we should practice trust in the digital world, I.e., how trust is performed.

- Participants learned how to use ratings, reviews and social distance to evaluate whether to trust a stranger. These characteristics are not neutral, they are *engineered* by the platform(s).

  - Roberto, a man from Milan in his 30s that was a user of a now defunct platform called CouchSurfing, told us, *"Every time you write a message, there is a message that it is recorded for safety reasons. This is guaranteed and it's important because it's true that strangers are friends that you haven't met yet, but at the same time, strangers are always strangers."* (Parigi & State, 2014)

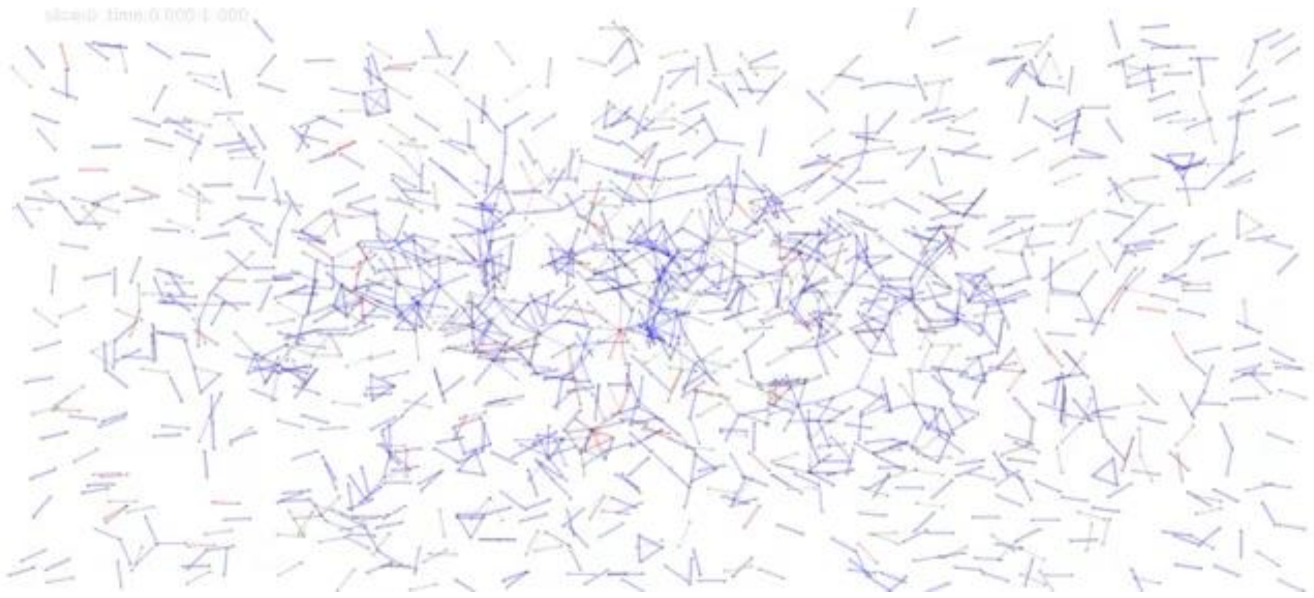
- What the platform(s) are teaching us is how to trust through metrics and technology—a fully disenchanted world.

  - Peter, a new CouchSurfer in his 20s from Reykjavik, told us, "I will check my references. That's the only [...] thing that I learned—just check people's references." (Parigi & State, 2014)

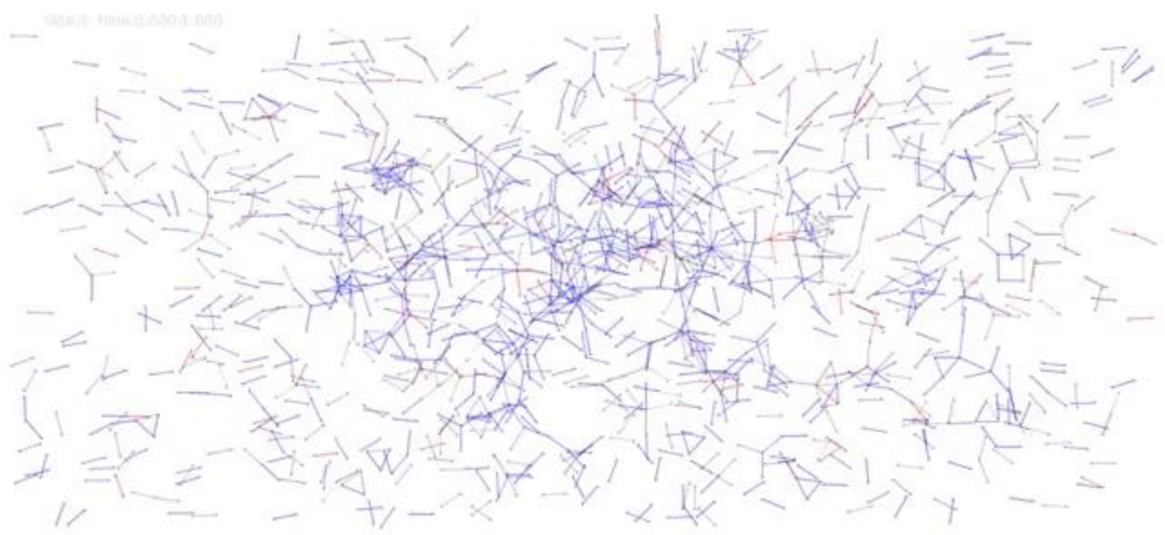
Friendship ties among Couchsurfers (2003 - 2011)

San Francisco

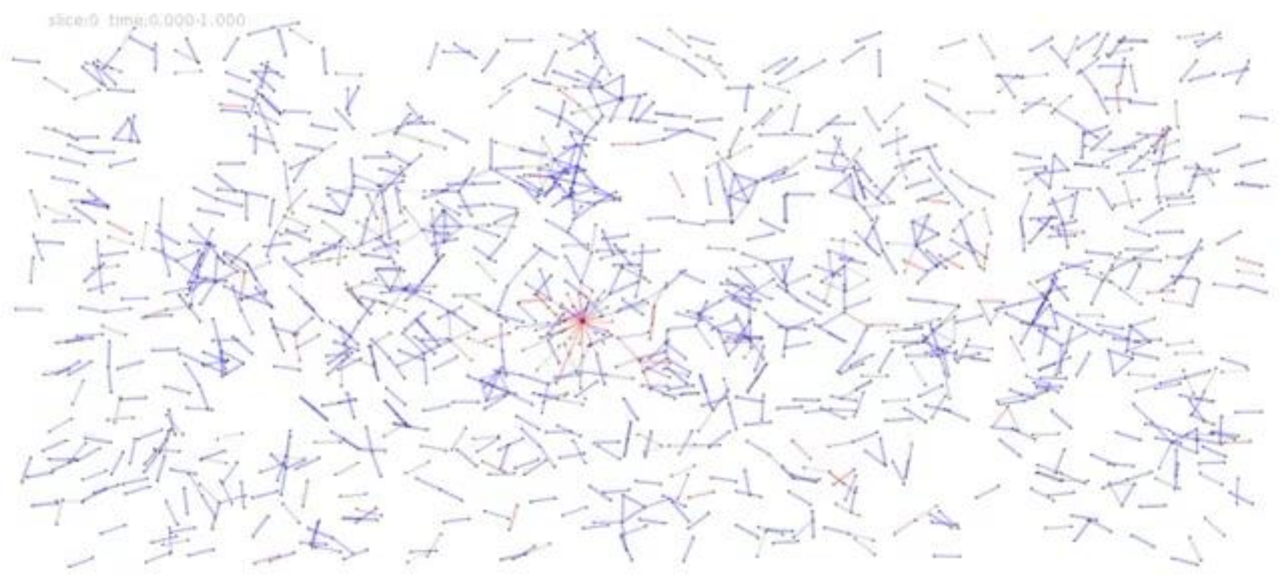
Berlin



Istanbul



Paris



Parigi, P., B. State. 2014 “Disenchanting the world: The impact of technology on relationships.” Conferences on Social Informatics

What is the role of the social sciences in a world with Platforms?

Related work

Abrahao, B., & Parigi, P. (2020). Computational social science, big data and networks. In R. Light & J. Moody (Eds.), The Oxford Handbook of Social Networks (pp. 516-534). Oxford University Press. (Stanford University)

Mogamma, Julie Mehretu. 1970

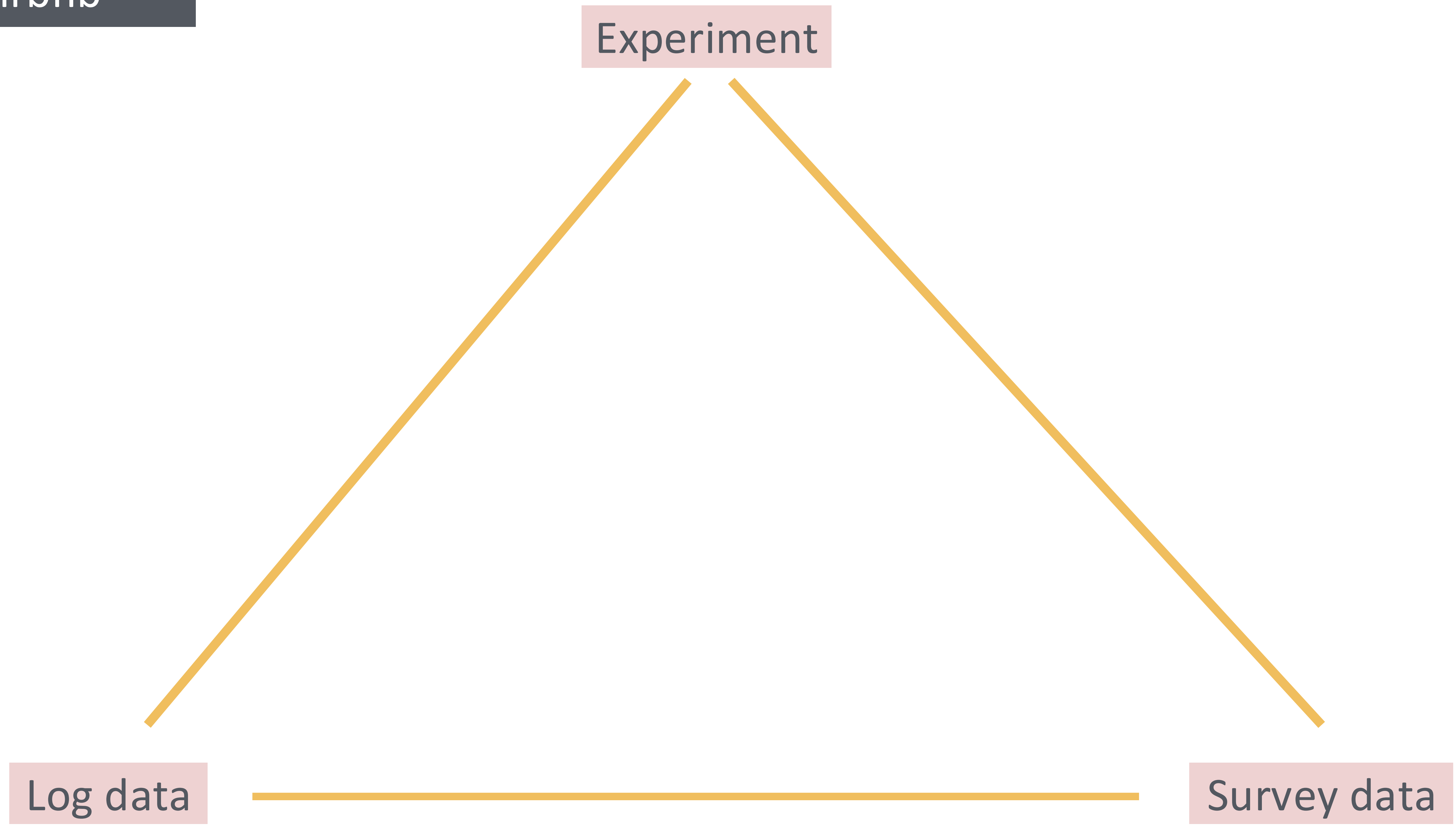
3. A quantifiable world

A new role for social scientists … are we ready ?

A new role for social scientists is possible where *we* experiment on interactions, mitigate the consequences of products and, broadly, operate in the world and not only observe it:

- Auguste Comte saw Sociology as the science for designing society.
  - *“There is no inquiry which is not finally reducible to a question of Numbers; for there is none which may not be conceived of as consisting in the determination of quantities by each other, according to certain relations.”* (Comte, *Mathematics* in Martineau, The Positive Philosophy of Auguste Comete).
- This is now more possible than ever but… are *we* ready for it?
  - *When things go bad*: The 2014 study from Jeff Hancock et al. that manipulated users’ newsfeeds to test emotional contagion.

Example from my work at Airbnb



Three types of data:

1. Experimental data on a trust game (~6,000 users)

2. Survey from users of the platform that did not participate in the experiment (~200,000 users)

3. Log data for #1 and #2

Barbosa, N. Sun, E., Antin, J. P. Parigi. 2020. “Designing for Trust, A behavioral framework for Sharing Economy Platforms.” WWW’20

Data triangulation

Features selection and convergent validity

Step1 : Train an ordinal classification model on the experimental sample

- Input: behavioral features Xi (clicks, stays, messages, etc.)
- Target: trust propensity Ti from the investment game (Low / High)
- The model (F) maps behavior → predicted trust propensity
  - The model uses LASSO regression to identify major behavioral features

Step 2: Predict trust in survey data using the behavioral model

- For each survey respondent j:
- Take their behavioral vector Xj'
- Compute predicted trust: Tj = F(Xj') (*as if they took part of the experiment*)
  - Use Deep Learning Neural Networks to train a classifier using the behavioral features

Step 3: Compare behavioral and attitudinal trust

- Group survey respondents by self-reported trust attitude (e.g. 1–2 = Low, 4–5 = High)
- Compare the average predicted trust between attitude groups:

Survey Constructs	Avg. Prediction
How trustworthy are Airbnb guests?	
High (4-5)	2.14
Low (1-2)	2.07
How safe do you feel when hosting guests in your listing(s) with Airbnb?	
High (4-5)	2.16
Low (1-2)	2.06
Trust Airbnb if things go wrong	
High (4-5)	2.14
Low (1-2)	2.07

Model Performance

PREDICTIONS FROM DEEP LEARNING MODEL

Metric	Guest Model	Host Model
Training Accuracy	0.78	0.78
Validation Accuracy during Training (20% split)	0.77	0.77
Validation Precision	0.78	0.79
Validation Recall	0.85	0.81
Validation F-1 (Hamming Loss)	0.81	0.81
Validation Hamming Loss	0.26	0.26
Test Precision	0.79	0.76
Test Recall	0.86	0.81
Test F-1 (Hamming Loss)	0.82	0.82
Test Hamming Loss	0.25	0.25
Best Thresholds	[0, .6145, .3781]	[0, .5922, .3873]

Pipeline

Experiment

Investment game involving host and guest profiles (US and Canada) N = 4,499

Feature Selection

Create a wide data set with behavioral signals based on theories of trust; use Lasso for feature selection

Triangulation

Do selected features also associate with other data sets on trust and safety?

Model Selection

Select best performance among difference machine learning algorithms

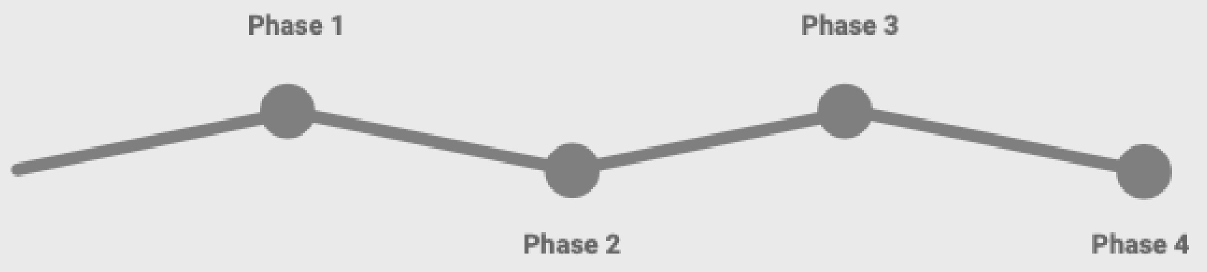
Training

Train the best model with selected features to predict an individual's propensity to trust other users

1

Generate Explanatory Model

How do low and high trust users behave throughout the user journey?



2

Generate Predictive Model

Make predictions on new users, classifying them as low-trust, medium-trust, and high-trust.

Group	High:Low Trust Ratio
1	.18
2	1.1

Trust	Behavior **1**	...	Behavior **n**
Low	2.5	...	3
High	1.78	....	3.2

Designing interactions

From observing to intervening

A new role for social scientists comes with ethical questions

Ethical tensions

- Privacy: behavioral inference (likes, clicks, posts) reveals identity traits beyond consent.
- Consent: platform participation ≠ informed participation.
- Fairness: biased data → biased algorithms (COMPAS sentencing case).
- Reproducibility: corporate data opacity blocks verification of results.

Abrahao, B. P. Parigi. 2021. "Computational Social Science, Big Data and Networks", in J. Moody (ed) The Oxford handbook of Social Networks.

Thank you!

References

Foundations / Disenchantment

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Trust as Attitude vs Practice

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Platform Society / Quantification

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My work

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- Barbosa, N. et al. (2020). “Designing for Trust: A Behavioral Framework for Sharing Economy Platforms.” In The Web Conference (WWW 2020)
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Features Selected

18 FOR GUESTS, 11 FOR HOSTS

Examples of host features

Less trust
Exchanging messages
Rejecting requests to stay
Visiting guest profiles

Behavior exhibited by individuals with low trust propensity.

In other words, these features may be helping users build trust.

More trust
Previous hosting activity
Relaxing requirements for booking
Receiving high ratings
Hosting new users

Behavior exhibited by individuals with high trust propensity.

Individuals exhibiting this behavior are more likely to trust others.

Predicting the behavior: Deep Learning Model

- Ordinal Multiclass Problem
  - Low < Medium < High Trust
  - Sigmoid activation function; binary cross entropy loss
  - Batch size = 32, Epochs = 1,000 with Early Stopping
  - Layers: (Input, no. of features selected by Lasso, 3)

- One model for hosts, one model for guests
- 60% training, 30% validation, 10% test

- **Ordinal encoding:** [1,0,0] = low, [1,1,0] = medium, [1,1,1] = high
- Prediction: [p(low) >= T_{low}, p(medium) >= T_{medium}, p(high) >= T_{high}]

- Ts are found by choosing highest F-1 score on predictions with tested column-wise thresholds in the interval [0,1] by 0.0001 increases.