RSM Erasmus | Rotterdam School of Management Erasmus University

AoM PDW – Next Decade Bot Research

Carolina A. de Lima Salge

Anna Priante

Aaron Schecter

Terry College of Business
UNIVERSITY OF GEORGIA

RSM Erasmus | Rotterdam School of Management Erasmus University

Terry College of Business UNIVERSITY OF GEORGIA

Agenda

Present a theoretical framework for bot delegation

Discuss the implications of generative AI for research on bots

Consider how bots can be leveraged for experimental research

Talk about how to take bot research into new uncharted territories

We also seek to maintain an interdisciplinary community of scholars who research the topic

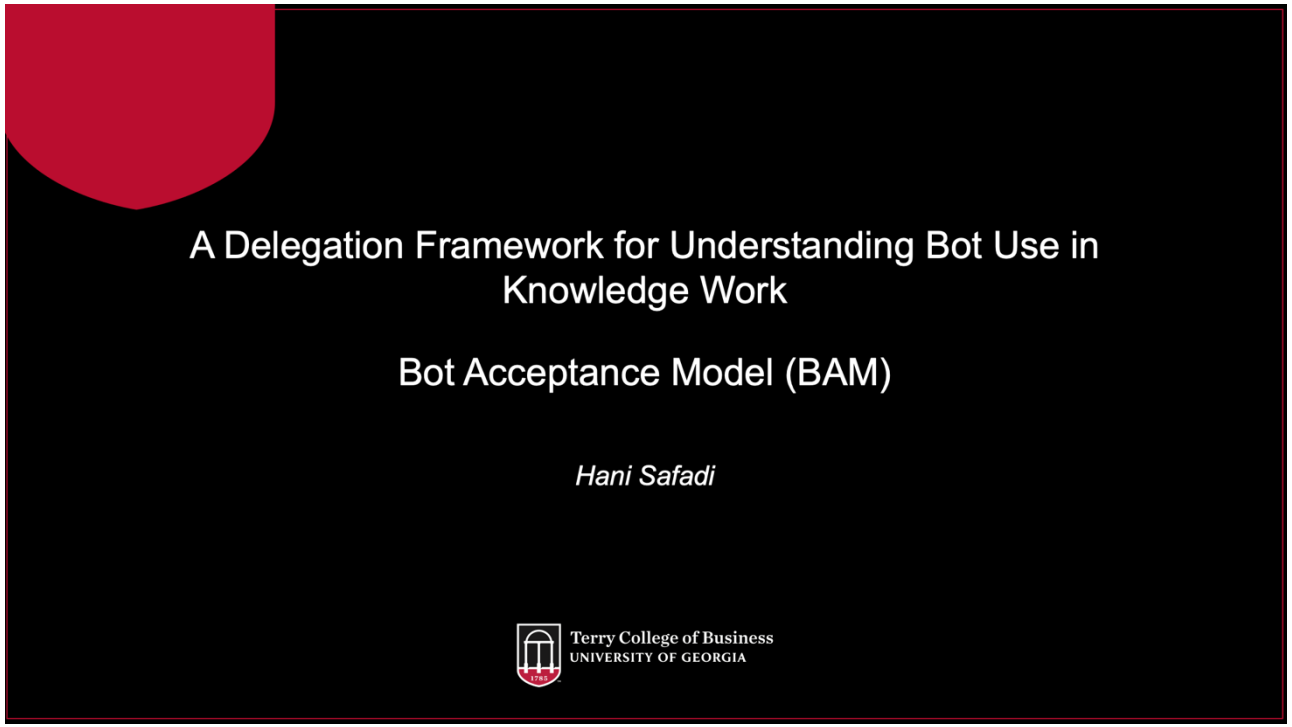
Presentations (~60 min)

Panel (~30 min)

Presentations

Hani Safadi

University of Georgia



RSM Erasmus | Rotterdam School of Management Erasmus University

Terry College of Business UNIVERSITY OF GEORGIA

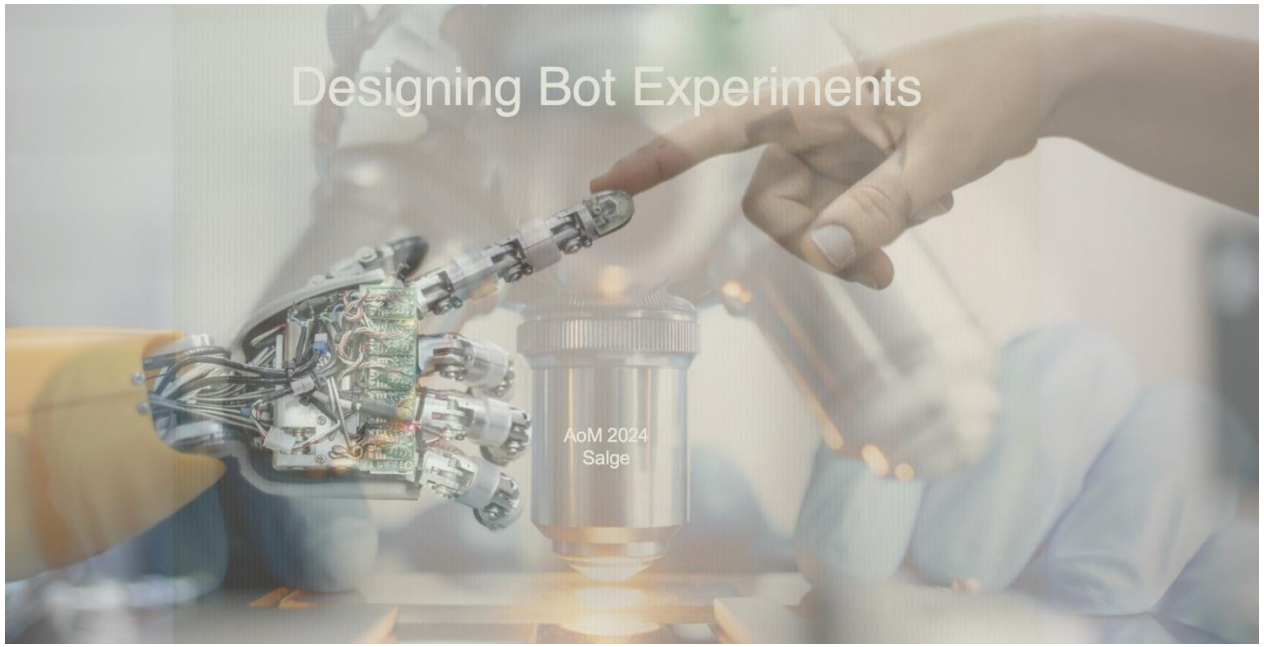
Presentations

Aaron Schecter
University of Georgia

RSM Erasmus | Rotterdam School of Management Erasmus University

Terry College of Business UNIVERSITY OF GEORGIA

Presentations



Carolina A. de Lima Salge
University of Georgia

RSM Erasmus | Rotterdam School of Management
Erasmus University

Terry College of Business
UNIVERSITY OF GEORGIA

Presentations

Jason B. Thatcher

University of Colorado Boulder

RSM Erasmus | Rotterdam School of Management Erasmus University

Terry College of Business UNIVERSITY OF GEORGIA

Panel

Hani Safadi
UGA

Anna Priante
RSM

Lior Zalmanson
Tel Aviv University

Jason Thatcher
UC Boulder

Carolina Salge
UGA

Aaron Schecter
UGA

RSM Erasmus | Rotterdam School of Management Erasmus University

Terry College of Business
UNIVERSITY OF GEORGIA

A Delegation Framework for Understanding Bot Use in Knowledge Work

Bot Acceptance Model (BAM)

Hani Safadi

Terry College of Business
UNIVERSITY OF GEORGIA

Bots in Online Communities

"There are many different types of bots, and their capabilities are a moving target. While advancements in artificial intelligence are drawing more attention to bots, many mainstream bots are still largely rule-based."

Safadi, Lalor, & Berente (MISQ forthcoming)

Q: Why do we still not have more agentic bots in online communities

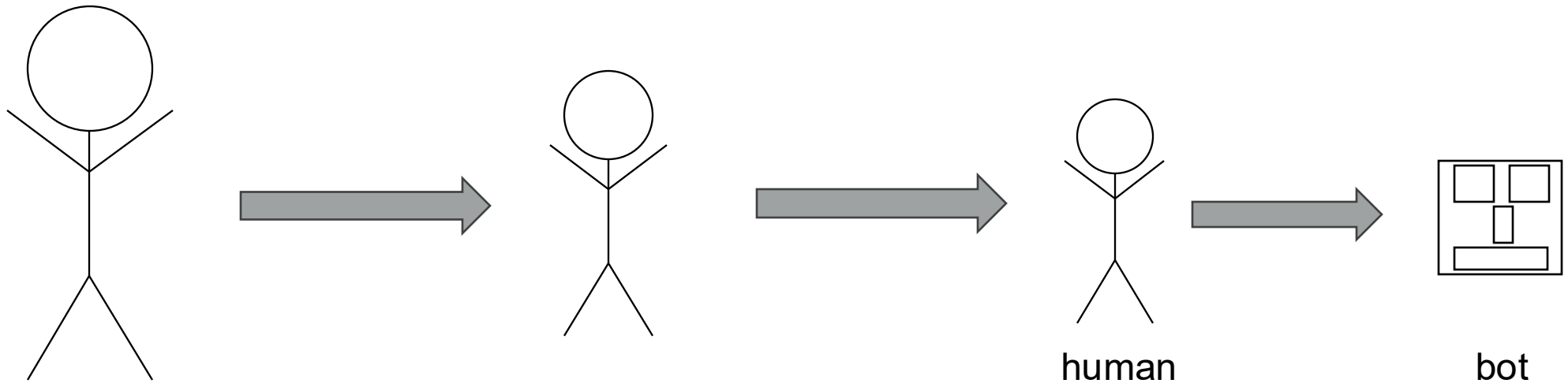
Table 1. Agentic IS Artifact Archetypes

	Agentic Archetypes	Examples	What's Different?
(limited decision-making latitude)	**Reflexive** (i.e., reactive)	• Sensing and acting (or alerting) agents, e.g., rebalance a financial portfolio when specified allocations are out of balance • Virtual assistants that react to queries (e.g., voice-based assistants)	These agents act reflexively, in direct response to relevant stimuli. Decisions are limited to models that define how to respond to expected stimuli.
	Supervisory (i.e., control system)	• Behavior modification systems (e.g., decision support, ambient intelligence, health behavior nudges, or financial trade suggestions) • Guidance systems such as those that observe human behaviors and remind them of process steps (e.g., visual cues, such as from smart lights, that guide how to put together furniture)	Supervisory agents evaluate deviations from the norm (or the status of goal progression) and seek to guide decision making or take actions that will help return to the norm or enhance probability of progression toward a specified goal.
	Anticipatory (i.e., proactive)	• Social media content searching, filtering, and presentation • Digital content compilation (e.g., automatic video or album creation) • Wearable augmented reality agents that anticipate needs (e.g., provide names for people in the field of view)	Anticipatory agents proactively apply model-based "reasoning" to anticipate needs or wants (e.g., the artifact automatically generates media compilations).
(expansive decision-making latitude)	**Prescriptive** (i.e., autonomous decision-making)	• Bots (e.g., chatbots, search bots, resume filtering bots, etc.) • Autonomous vehicles • Automated financial portfolio management • Legal agents (e.g., arbitration or even judicial decision prescription) • Medical agents (e.g., that make decisions during procedures)	Prescriptive agents act as substitutes for either behavior-based decision-making or outcome-based decision making by prescribing or taking actions.

Baird, A., & Maruping, L. M. (2021)

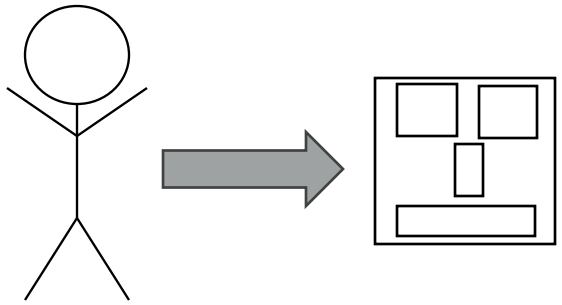
Delegation of Decision Making

- Decision rights delegation: assigning authority to make specific decisions to different individuals or departments within an organization (Tiwana & Kim 2015; Kirsch 1997; Weber, Simon, Barnard)

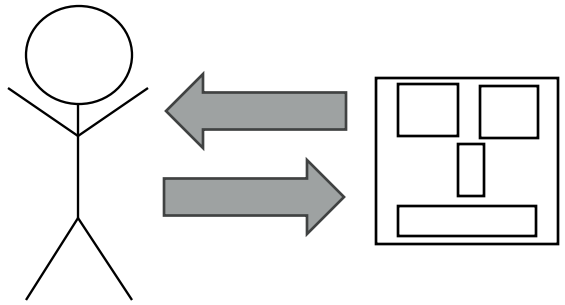


How do People Delegate to Bots?

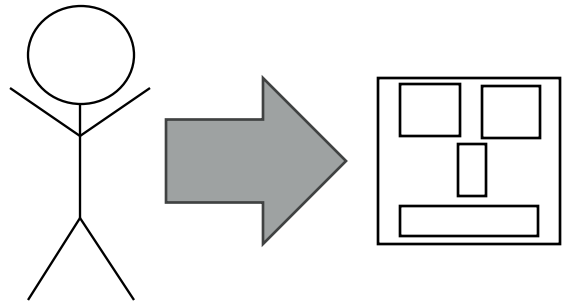
Centaur



Cyborg



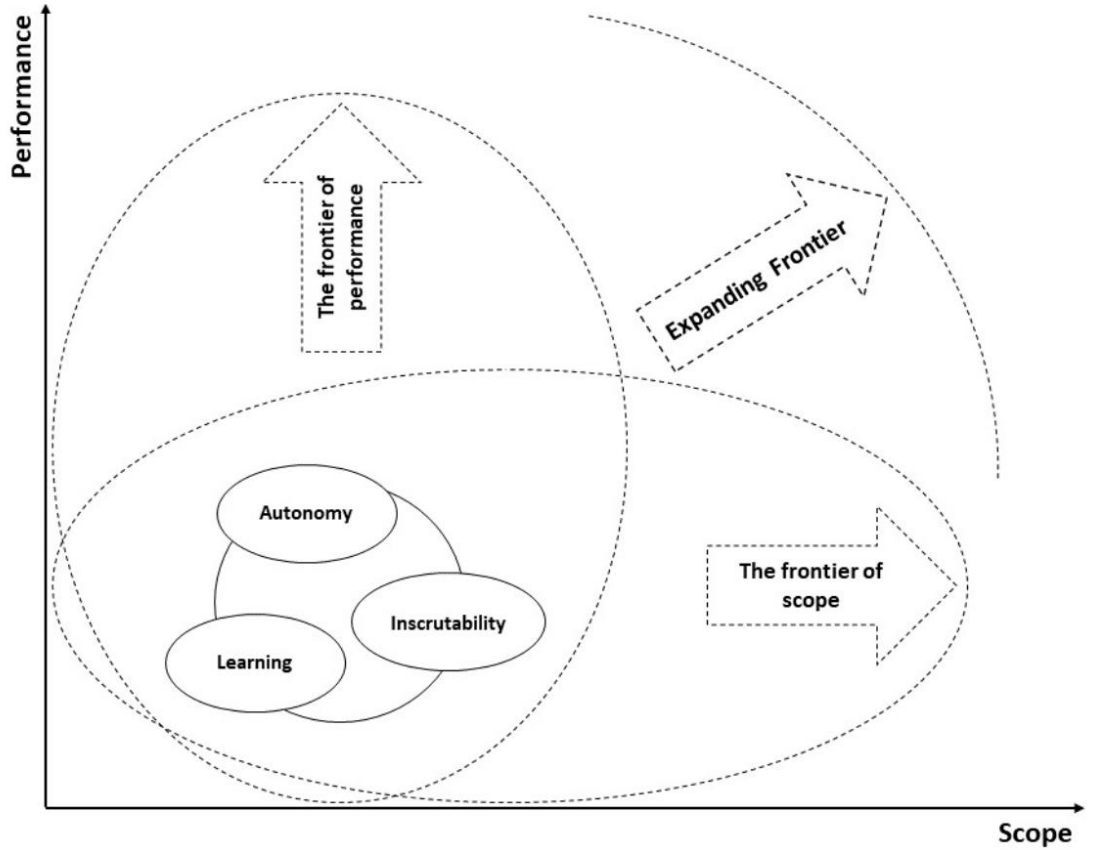
Self-automator



Dell'Acqua, F., McFowland, E., Mollick, E. R., Lifshitz-Assaf, H., Kellogg, K., Rajendran, S., Krayer, L., Candelon, F., & Lakhani, K. R. (2023). Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality.

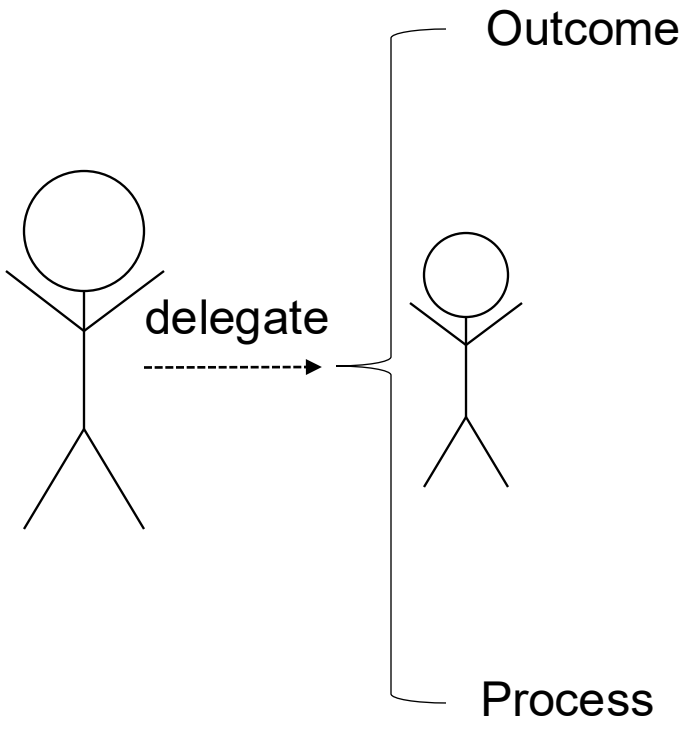
Why do People not Delegate More to Bots?

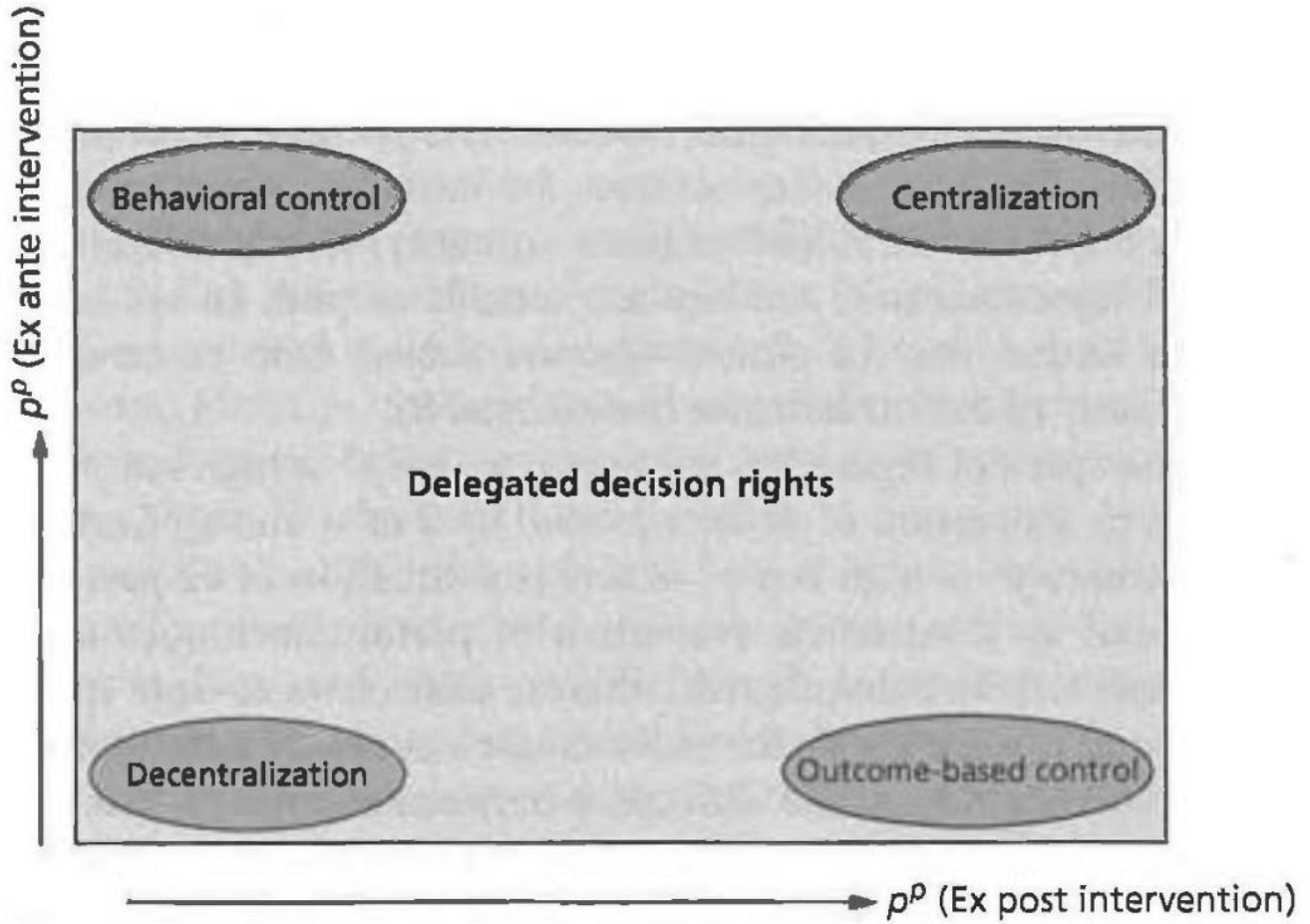
- Mainstream MIS theories
  - Technology acceptance model
  - Task technology fit
  - Expectation confirmation
  - …
- New perspectives
  - Aversion
  - Transparency
  - Learning
  - Inscrutability
  - …



Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing Artificial Intelligence. *MIS Quarterly*, *45*(3).

Delegation Modes



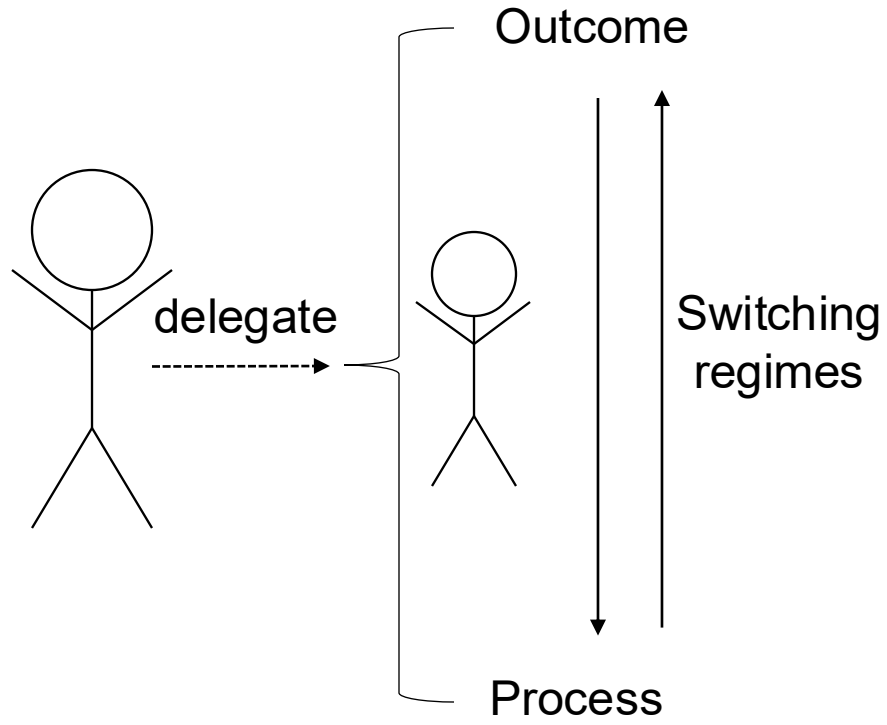


Puranam, P. (2018). *The microstructure of organizations*. Oxford University Press.

- Outcome control: medical diagnosis, self-driving cars
- Process control: hiring, judicial & policing systems

Delegation Failure

- Switching regimes: moving within the space of delegation possibilities based on some conditions, rather than fixed intervention probabilities (Puranam 2018 Ch5).
- **Delegation failure: a persistent switching regime**



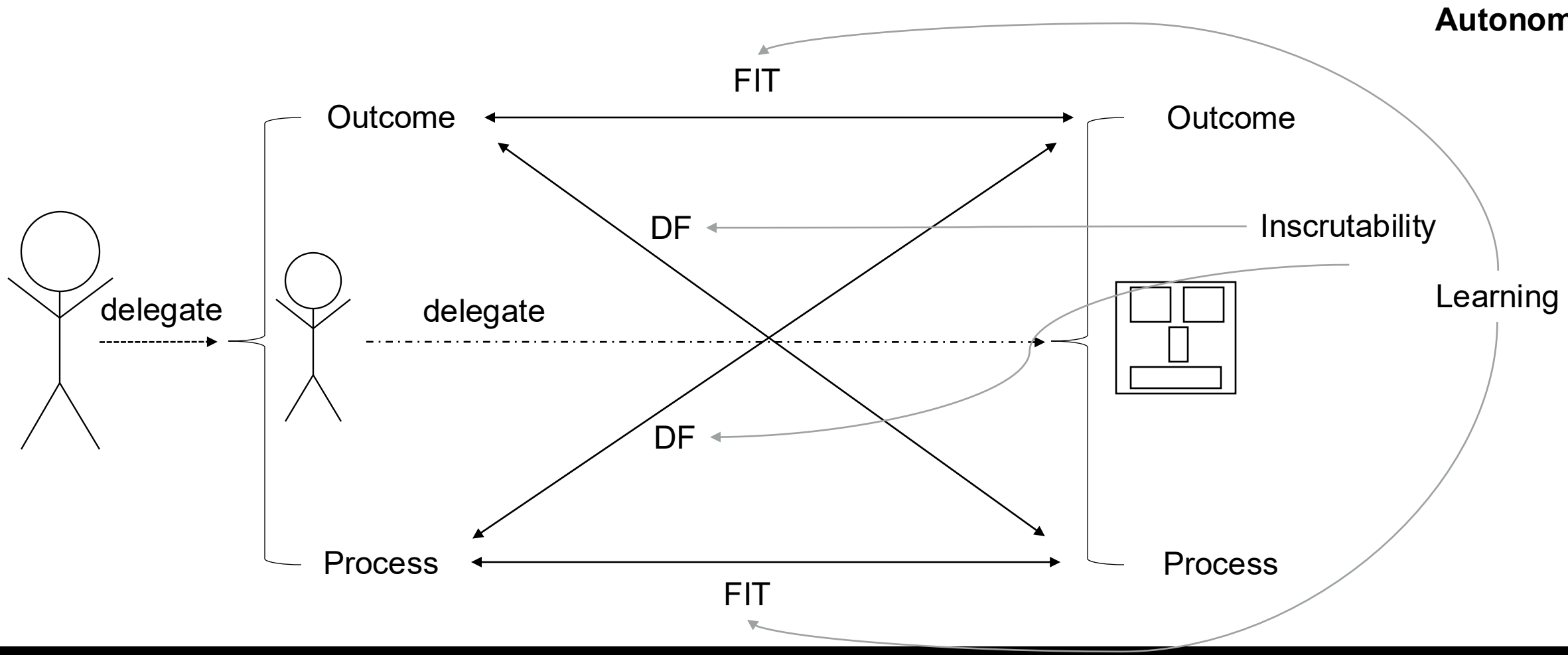
More agentic bots ⇔ Generative AI

- Predictability
- Stochasticness
- Randomness

To Engage or Not to Engage with AI for Critical Judgments: How Professionals Deal with Opacity When Using AI for Medical Diagnosis

Sarah Lebovitz,[a] Hila Lifshitz-Assaf,[b] Natalia Levina[b]

Delegation Failure Framework



Generative AI and Bot Research

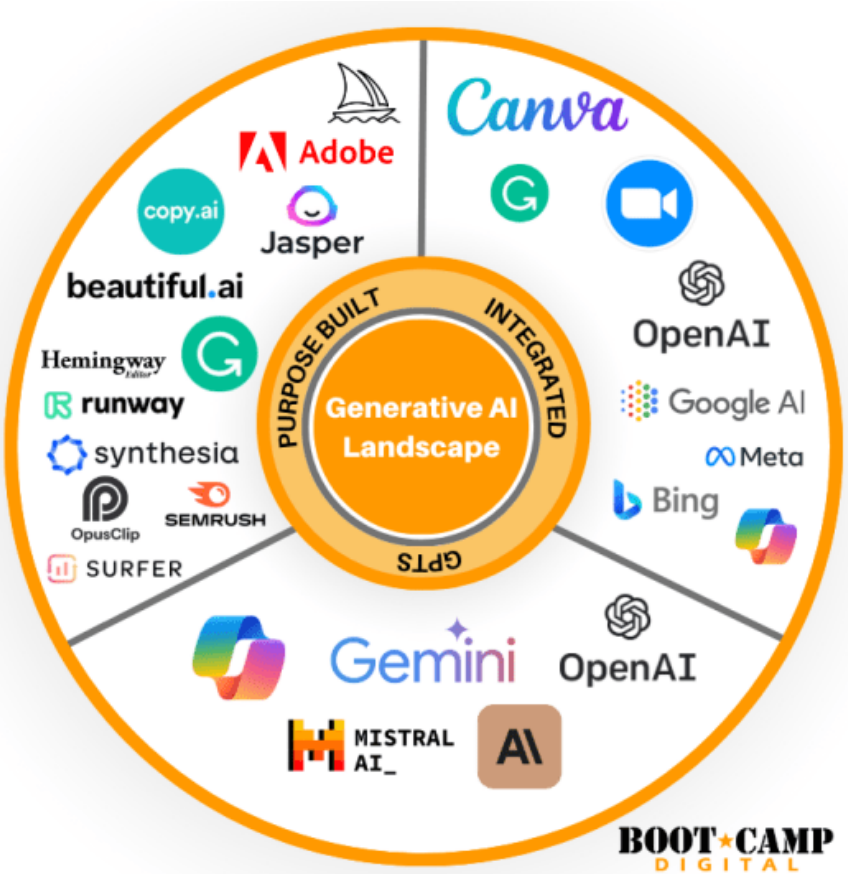
Aaron Schecter

Department of Management Information Systems

University of Georgia, Terry College of Business

What is Generative AI?

- AI that can **generate new content** (text, images, etc.) based on the data it has been trained on.
- Key features include
  - Capacity for creativity, in the sense of unique or unexpected outcomes
  - Interactivity and understanding of context
  - Ability to leverage huge amounts of data



https://bootcampdigital.com/blog/generative-ai-landscape-and-ecosystem/

Comparing GenAI to Traditional Bots

Automated Bots
- Rule-based systems
- Pre-programmed responses or actions
- Limited adaptability
- No ability for sensemaking

Generative AI
- AI-driven content creation
- Real-time adaptation and response
- Can simulate human-like creativity and problem-solving
- Illusion of sensemaking

Uses of GenAI for Research

- GenAI can be used for many elements of the research process
  - Summarizing literature
  - Writing code
  - Analyzing data
  - Creating figures
  - Crafting hypotheses
- GenAI can also be deployed as a bot to facilitate research
  - Interactive chatbots or assistants
  - Virtual teammates
  - Interviewers
  - Participants in studies

Literature Review

Jarrahi et al 2023.pdf
PDF

Summarize this article and provide the key takeaways

Summary of the Article

The article "Artificial Intelligence: A Strategy to Harness its Power through Organizational Learning" by Mohammad Hossein Jarrahi and colleagues explores how organizations can strategically leverage artificial intelligence (AI) by aligning it with organizational learning processes. The authors argue that to fully realize the potential of AI, organizations must move beyond viewing AI as a tool for specific tasks and instead integrate it into the broader strategic framework of the organization.

Key Takeaways

1. **Strategic Significance of AI**:
   - AI's potential is often underutilized due to its implementation in siloed operations rather than as a strategic asset. The power of AI lies in its self-learning capabilities, which can be harnessed to create long-term business gains.
2. **Learning-Centered Approach**:
   - The authors propose a learning-centered approach where AI's self-learning capabilities

give me an overview of the literature on algorithmic aversion

Searched 2 sites

Overview of the Literature on Algorithmic Aversion

Algorithmic aversion refers to the phenomenon where individuals prefer human judgment over algorithmic decisions, even when algorithms are demonstrably more accurate. Research indicates several key factors influencing this aversion:

1. **Perceived Lack of Transparency**: People tend to trust systems they understand, and algorithms are often seen as "black boxes," leading to discomfort and mistrust.
2. **Error Intolerance**: While humans are more forgiving of errors made by other humans, algorithmic errors are often judged more harshly, reinforcing aversion.
3. **Lack of Control**: Users tend to prefer systems where they have some level of control or influence over the outcome. The absence of such control in algorithmic systems can heighten aversion.
4. **Cultural and Contextual Factors**: Cultural background and the specific context in which an algorithm is applied also play significant roles in whether people accept or reject algorithmic decisions.
5. **Strategies to Mitigate Aversion**: Research suggests that providing users with more information

Automated Analyses

Load the 'Boston' dataset fr
model to predict the variab
metrics, and diagnostic plot

Diagnostic Plots

The diagnostic plots displayed above i

1. **Residual Plot**: Shows the residual
2. **Q-Q Plot**: Checks if the residuals a
3. **Scale-Location Plot**: Plots the squ
   to check the homoscedasticity.
4. **Leverage Plot**: Identifies influenti
   model.

These plots help assess the assumptio
homoscedasticity, and the influence o
with an R-squared value of approxima
can be explained by the model's predi

Analysis

python | Always show details | Copy code

```
import pandas as pd
import statsmodels.api as sm
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.datasets import load_boston
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, r2_score

# Load the dataset
boston = load_boston()
boston_df = pd.DataFrame(boston.data, columns=boston.feature_n
boston_df['medv'] = boston.target

# Define the predictor variables (X) and the response variable
X = boston_df.drop(columns=['medv'])
y = boston_df['medv']

# Add a constant to the predictor variables matrix (for the in
```

Use a certain information technology

Regression Model Summary

efficients:

Intercept: 30.246751
CRIM: -0.113056
ZN: 0.030110
INDUS: 0.040381
CHAS: 2.784438
NOX: -17.202633
RM: 4.438835
AGE: -0.006296
DIS: -1.447865
RAD: 0.262430
TAX: -0.010647
PTRATIO: -0.915456
B: 0.012351
LST

Can you show more dataset examples?

The University of Georgia
TERRY COLLEGE OF BUSINESS

Automated Theorizing?

We are safe…for now ;)

Generate a theoretical explanation for why people might choose to use a certain information technology

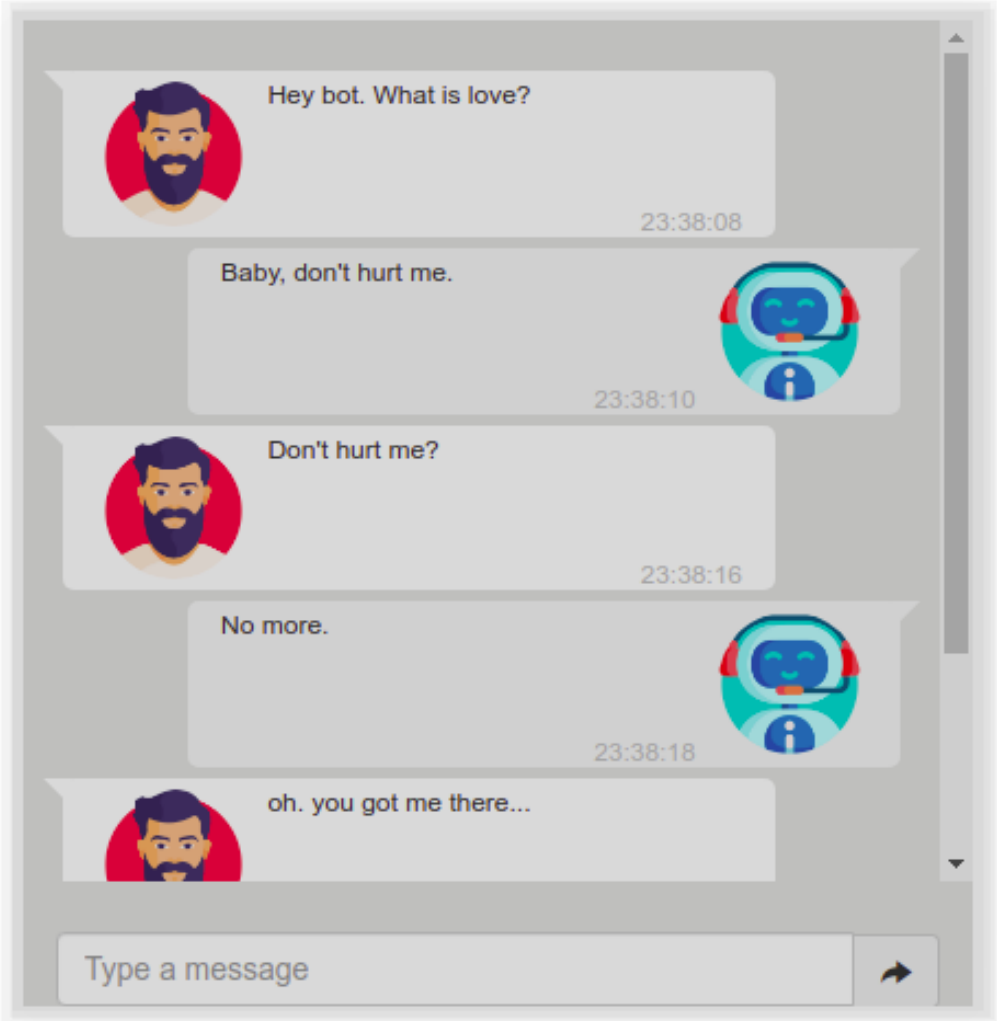
Theoretical Explanation for Adoption of Information Technology

The decision to adopt and use a particular information technology (IT) can be influenced by a variety of theoretical frameworks. Here are some key theories that explain why individuals and organizations might choose to use certain IT:

1. **Technology Acceptance Model (TAM)**
   - **Perceived Usefulness (PU)**: This refers to the extent to which a person believes that using the technology will enhance their job performance. If the IT can make tasks easier, faster, or more efficient, people are more likely to adopt it.
   - **Perceived Ease of Use (PEOU)**: This is the degree to which a person believes that using the technology will be free from effort. Technologies that are user-friendly and easy to learn are more likely to be accepted.
2. **Unified Theory of Acceptance and Use of Technology (UTAUT)**
   - **Performance Expectancy**: Similar to perceived usefulness, this is the belief that the

Chatbots

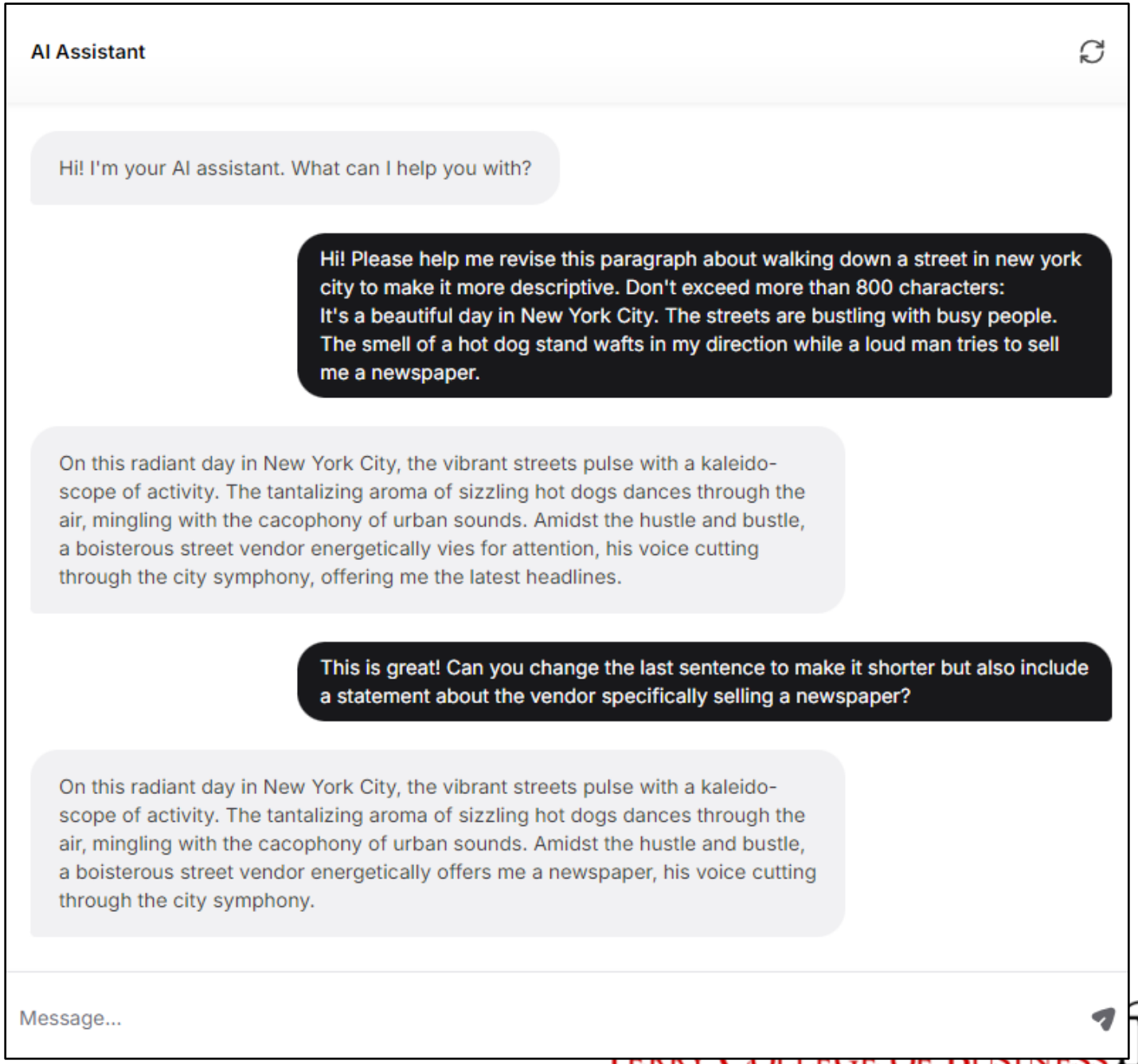
- A chatbot is essentially an interface through which a user communicates with the bot
  - The bot can be preprogrammed to give certain responses based on specific queries
  - The bot can use varying degrees of natural language processing to both i) parse unstructured user inputs, and/or ii) provide unique responses
- Chatbots can be used to scale up interview research
- Chatbots can be used to uncover potentially sensitive information from individuals



Credit: https://towardsdatascience.com/develop-a-conversational-ai-bot-in-4-simple-steps-1b57e98372e2?gi=f4246ad442ff

AI as an Assistant

Chatbase



Virtual Teammates

- Bots can also be used as virtual teammates to help scale up small group research
- Organizational realities suggest we will be working with bots in some form in the future – how do we test the effects?
- Prior work has used primarily wizard of oz methods, simulations, or hypothetical cases
- Advancements in chatbot technology can now make a conversational agent more realistic and easier to deploy at scale

Credit: http://disneyexaminer.com/2016/06/03/i-talked-to-judy-hopps-on-facebook-messenger-and-she-trained-me-to-be-a-zpd-officer-imperson-chatbot/

Bots as Experimental Units

Large Language Models as Simulated Economic Agents:
What Can We Learn from *Homo Silicus*?*

John J. Horton
MIT & NBER

March 22, 2023

Turning large language models into cognitive models

Marcel Binz
MPRG Computational Principles of Intelligence
Max Planck Institute for Biological Cybernetics, Tübingen, Germany
marcel.binz@tue.mpg.de

Eric Schulz
MPRG Computational Principles of Intelligence
Max Planck Institute for Biological Cybernetics, Tübingen, Germany

Do LLM Agents Exhibit Social Behavior?

Yan Leng*
McCombs School of Business, The University of Texas at Austin, yan.leng@mccombs.utexas.edu
Yuan Yuan*
Daniels School of Business, Purdue University, yuanyuan@purdue.edu

A Word of Caution

Perspective

Artificial intelligence and illusions of understanding in scientific research

https://doi.org/10.1038/s41586-024-07146-0

Received: 31 July 2023

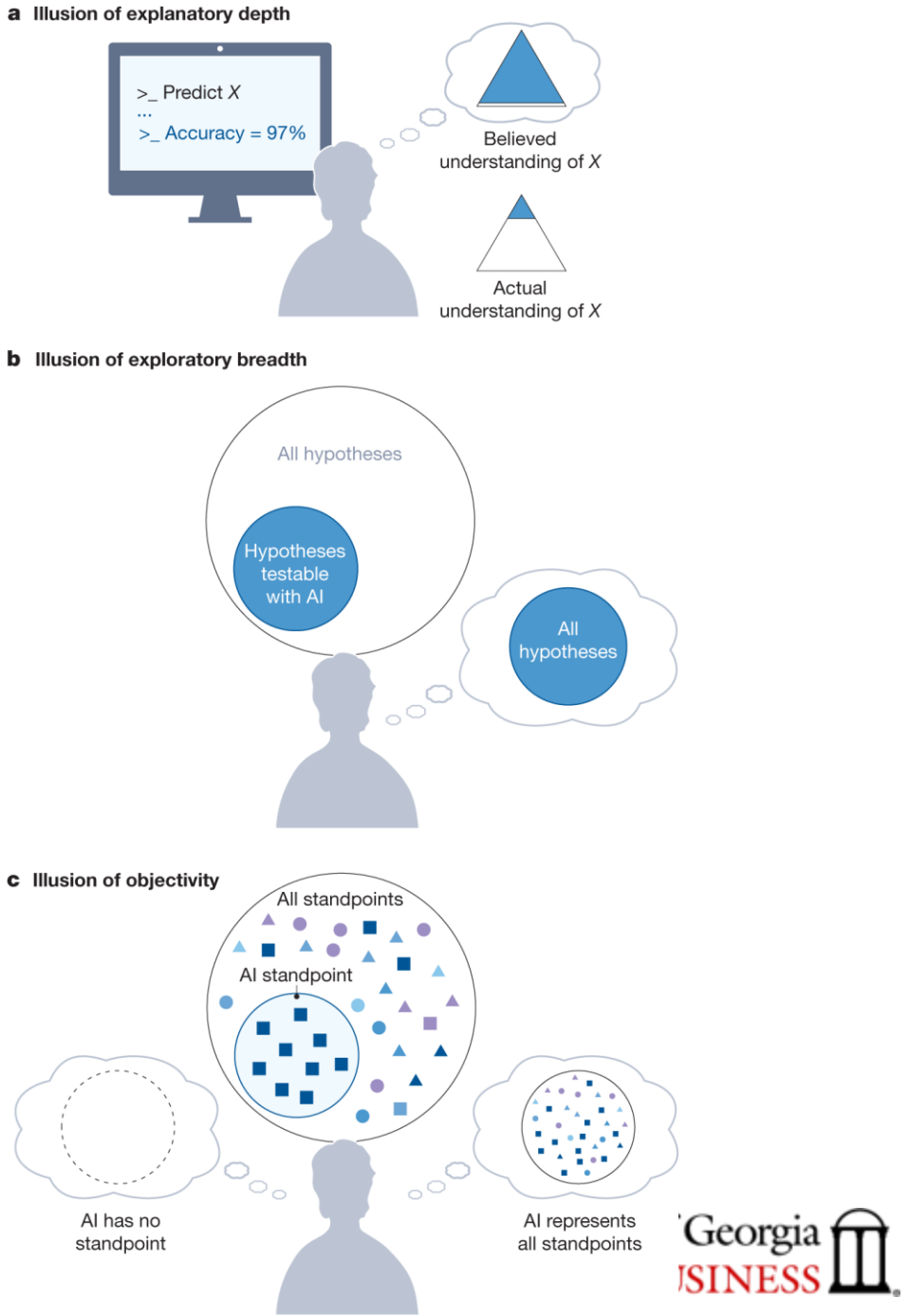
Accepted: 31 January 2024

Published online: 6 March 2024

Check for updates

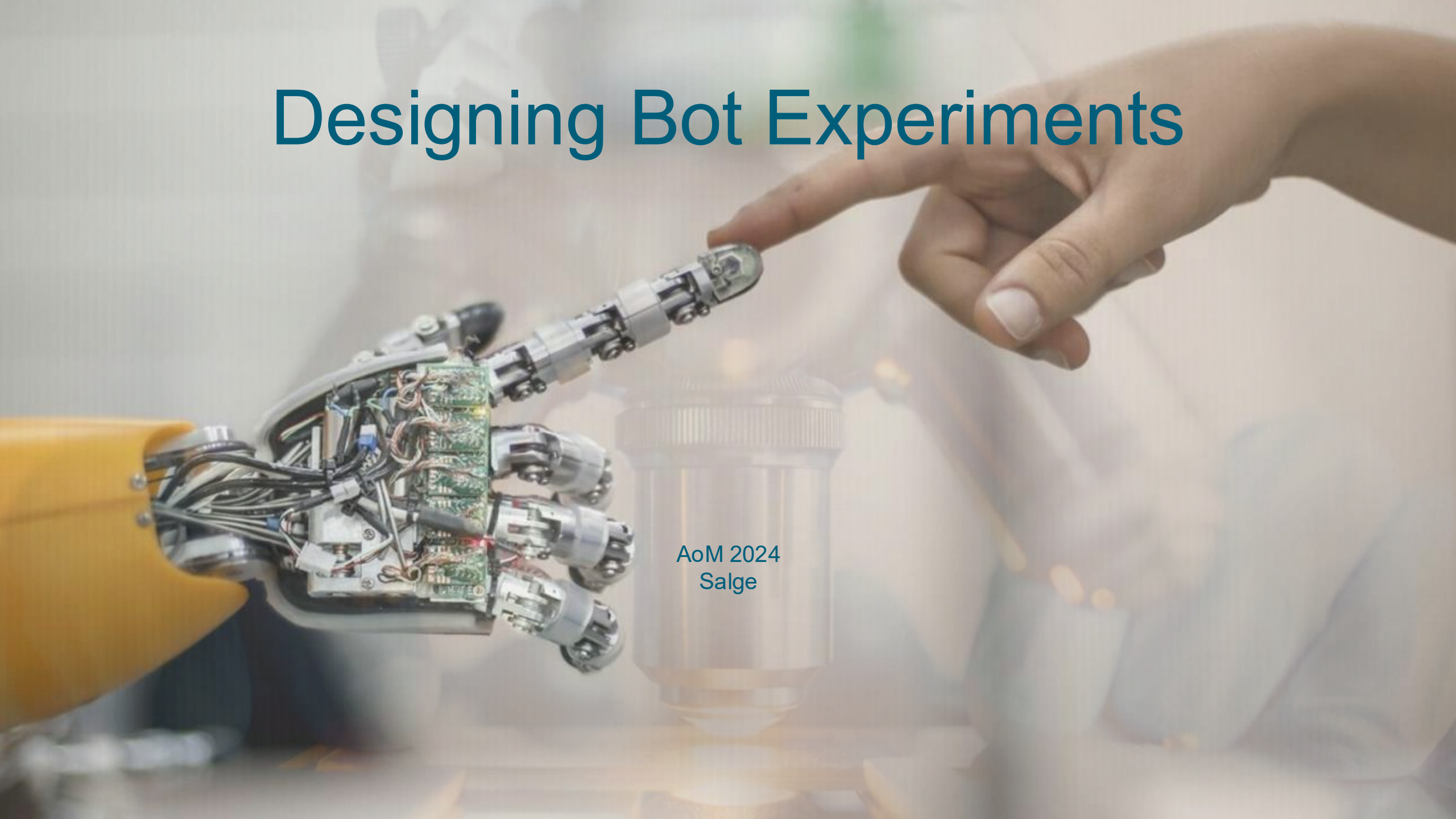
Lisa Messeri[1,4] & M. J. Crockett[2,3,4]

Scientists are enthusiastically imagining ways in which artificial intelligence (AI) tools might improve research. Why are AI tools so attractive and what are the risks of implementing them across the research pipeline? Here we develop a taxonomy of scientists' visions for AI, observing that their appeal comes from promises to improve productivity and objectivity by overcoming human shortcomings. But proposed AI solutions can also exploit our cognitive limitations, making us vulnerable to illusions of understanding in which we believe we understand more about the world than we actually do. Such illusions obscure the scientific community's ability to see the



Georgia BUSINESS

Designing Bot Experiments



AoM 2024
Salge

Designing Bot Experiments

- Whether you like it or not, experiments with bots are already happening and here to stay
- The operative question now becomes, how to do them well? That answer depends on two factors

Designing Bot Experiments

- Role of Bots
  - Treatment delegators
  - Treatment exposers
  - Bots as experimental subjects
  - ~~Bots as the treatment~~
- Validity Concerns (Shadish 2002)
  - Internal validity
  - External validity
  - Construct validity
  - …

Bots as “Treatment Delegators”

- Manage the process that determines which subjects receive which treatment and when

Bots as “Treatment Exposers”

- Expose subjects to different treatments

Bots as “Treatment Exposers”

PNAS

Exposure to opposing views on social media can increase political polarization

Christopher A. Bail[a,1], Lisa P. Argyle[b], Taylor W. Brown[a], John P. Bumpus[a], Haohan Chen[c], M. B. Fallin Hunzaker[d], Jaemin Lee[a], Marcus Mann[a], Friedolin Merhout[a], and Alexander Volfovsky[a]

[a]Department of Sociology, Duke University, Durham, NC 27708; [b]Department of Political Science, Brigham Young University, Provo, UT 84602; [c]Department of Political Science, Duke University, Durham, NC 27708; [d]Department of Sociology, New York University, New York, NY 10012; and [e]Department of Statistical Science, Duke University, Durham, NC 27708

Edited by Peter S. Bearman, Columbia University, New York, NY, and approved August 9, 2018 (received for review March 20, 2018)

There is mounting concern that social media sites contribute to political polarization by creating “echo chambers” that insulate people from opposing views about current events. We surveyed a large sample of Democrats and Republicans who visit Twitter at least three times each week about a range of social policy issues. One week later, we randomly assigned respondents to a treatment condition in which they were offered financial incentives to follow a Twitter bot for 1 month that exposed them to messages from those with opposing political ideologies (e.g., elected officials, opinion leaders, media organizations, and nonprofit groups). Respondents were resurveyed at the end of the month to measure the effect of this treatment, and at regular intervals throughout the study period to monitor treatment compliance. We find that Republicans who followed a liberal Twitter bot became substantially more conservative posttreatment. Democrats exhibited slight increases in liberal attitudes after following a conservative Twitter bot, although these effects are not statistically significant. Notwithstanding important limitations of our study, these findings have significant implications for the interdisciplinary literature on political polarization and the emerging field of computational social science.

political polarization | computational social science | social networks | social media | sociology

Political polarization in the United States has become a central focus of social scientists in recent decades (1–7). Americans are deeply divided on controversial issues such as inequality, gun control, and immigration—and divisions about such issues have become increasingly aligned with partisan identities in recent years (8, 9). Partisan identification now predicts preferences about a range of social policy issues nearly three times as well as any other demographic factor—such as education or age (10). These partisan divisions not only impede compromise in the design and implementation of social policies but also have far-reaching consequences for the effective function of democracy more broadly (11–15).

America’s cavernous partisan divides are often attributed to “echo chambers,” or patterns of information sharing that reinforce preexisting political beliefs by limiting exposure to opposing political views (16–20). Concern about selective exposure to information and political polarization has increased in the age of social media (16, 21–23). The vast majority of Americans now visit a social media site at least once each day, and a rapidly growing number of them list social media as their primary source of news (24). Despite initial optimism that social media might enable people to consume more heterogeneous sources of information about current events, there is growing concern that such forums exacerbate political polarization because of social network homophily, or the well-documented tendency of people to form social network ties to those who are similar to themselves (25, 26). The endogenous relationship between social network formation and political attitudes also creates formidable challenges for the study of social media echo chambers and political polarization, since it is notoriously difficult to establish whether social media networks shape political opinions, or vice versa (27–29).

Here, we report the results of a large field experiment designed to examine whether disrupting selective exposure to partisan information among Twitter users shapes their political attitudes. Our research is governed by three preregistered hypotheses. The first hypothesis is that disrupting selective exposure to partisan information will decrease political polarization because of intergroup contact effects. A vast literature indicates contact between opposing groups can challenge stereotypes that develop in the absence of positive interactions between them (30). Studies also indicate intergroup contact increases the likelihood of deliberation and political compromise (31–33). However, all of these previous studies examine interpersonal contact between members of rival groups. In contrast, our experiment creates virtual contact between members of the public and opinion leaders from the opposing political party on a social media site. It is not yet known whether such virtual contact creates the

Significance

Social media sites are often blamed for exacerbating political polarization by creating “echo chambers” that prevent people from being exposed to information that contradicts their preexisting beliefs. We conducted a field experiment that offered a large group of Democrats and Republicans financial compensation to follow bots that retweeted messages by elected officials and opinion leaders with opposing political views. Republican participants expressed substantially more conservative views after following a liberal Twitter bot, whereas Democrats’ attitudes became slightly more liberal after following a conservative Twitter bot—although this effect was not statistically significant. Despite several limitations, this study has important implications for the emerging field of computational social science and ongoing efforts to reduce political polarization online.

Author contributions: C.A.B., L.P.A., T.W.B., J.P.B., H.C., M.B.F.H., J.L., M.M., F.M., and A.V. designed research; C.A.B., L.P.A., T.W.B., H.C., M.B.F.H., J.L., M.M., and F.M. performed research; C.A.B., T.W.B., H.C., J.L., and A.V. contributed new reagents/analytic tools; C.A.B., L.P.A., T.W.B., H.C., M.B.F.H., J.L., M.M., F.M., and A.V. analyzed data; and C.A.B., L.P.A., T.W.B., M.B.F.H., M.M., F.M., and A.V. wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

Data deposition: All data, code, and the markdown file used to create this report will be available at this link on the Dataverse: https://dataverse.harvard.edu/dataverse.xhtml?alias=chris_bail.

[1]To whom correspondence should be addressed. Email: christopher.bail@duke.edu.

This article contains supporting information online at www.pnas.org/lookup/suppl/doi:10.1073/pnas.1804840115/-/DCSupplemental.

Published online August 28, 2018.

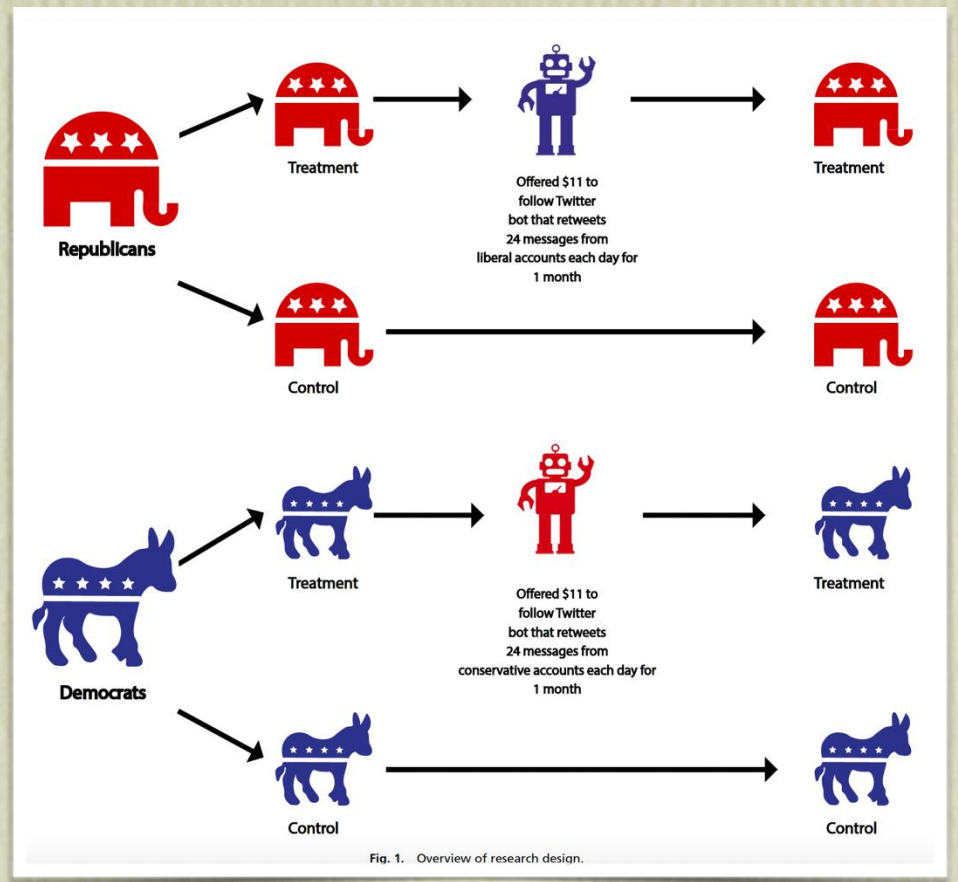
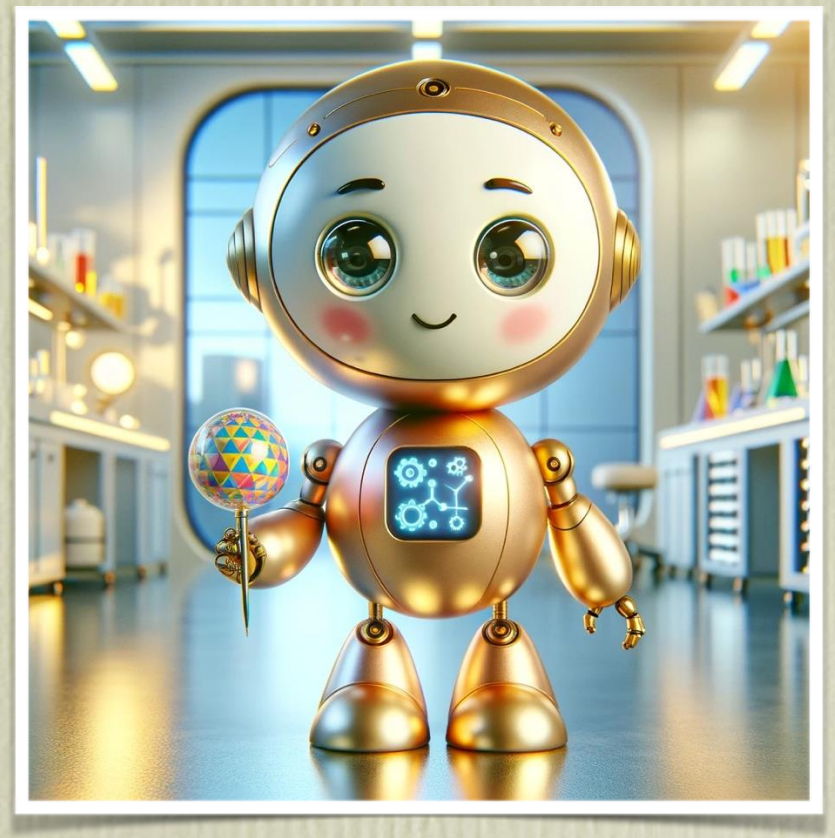


Fig. 1. Overview of research design.

Bots as “Experimental Subjects”

- Receive and respond to different treatments



Bots as “Experimental Subjects”

Automated Social Science:
Language Models as Scientist and Subjects*

Benjamin S. Manning† Kehang Zhu† John J. Horton
MIT Harvard MIT & NBER

April 17, 2024

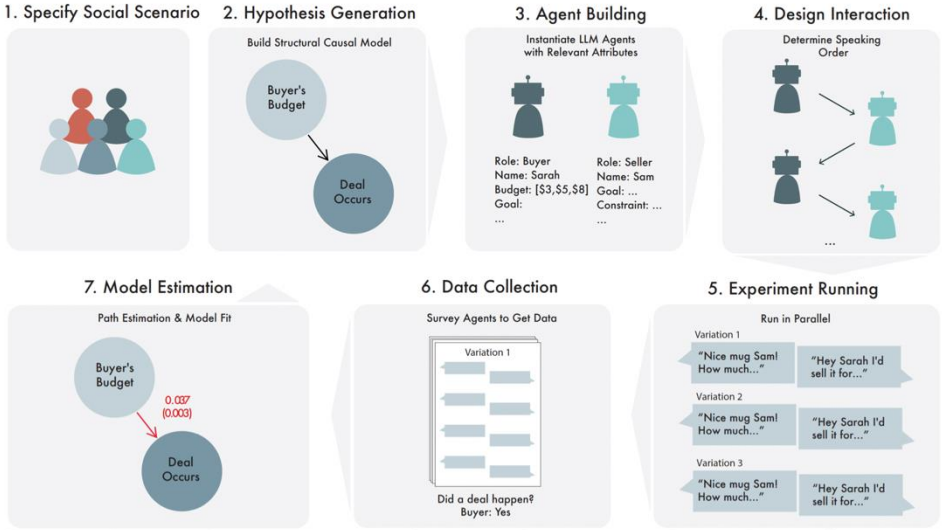
Abstract

We present an approach for automatically generating and testing, *in silico*, social scientific hypotheses. This automation is made possible by recent advances in large language models (LLM), but the key feature of the approach is the use of structural causal models. Structural causal models provide a language to state hypotheses, a blueprint for constructing LLM-based agents, an experimental design, and a plan for data analysis. The fitted structural causal model becomes an object available for prediction or the planning of follow-on experiments. We demonstrate the approach with several scenarios: a negotiation, a bail hearing, a job interview, and an auction. In each case, causal relationships are both proposed and tested by the system, finding evidence for some and not others. We provide evidence that the insights from these simulations of social interactions are not available to the LLM purely through direct elicitation. When given its proposed structural causal model for each scenario, the LLM is good at predicting the signs of estimated effects, but it cannot reliably predict the magnitudes of those estimates. In the auction experiment, the *in silico* simulation results closely match the predictions of auction theory, but elicited predictions of the clearing prices from the LLM are inaccurate. However, the LLM's predictions are dramatically improved if the model can condition on the fitted structural causal model. In short, the LLM knows more than it can (immediately) tell.

*Thanks to generous support from Drew Houston and his AI for Augmentation and Productivity seed grant. Thanks to Jordan Ellenberg, Benjamin Lira Luttges, David Holtz, Bruce Sacerdote, Paul Röttger, Mohammed Alsobay, Ray Duch, Matt Schwartz, David Autor, and Dean Eckles for their helpful feedback. Author's contact information, code, and data are currently or will be available at `http://www.benjaminmanning.io/`.

†Both authors contributed equally to this work.

Figure 1: An overview of the automated system.



Notes: Each step in the process corresponds to an analogous step in the social scientific process as done by humans. The development of the hypothesis guides the experimental design, execution, and model estimation. Researchers can edit the system's decisions at any step in the process.

Role	Alleviates concerns of…	Aggravates concerns of…
Delegator 	Internal Validity	NA
Exposer 	Internal Validity Statistical Validity	NA
Subject 	Internal Validity Construct Validity	External Validity Internal Validity

Role	Alleviates concerns of…	Aggravates concerns of…
Delegator 	Internal Validity	

- … and **ambiguous temporal precedence** in particular by assuring proper timing and randomization of treatments

Role	Alleviates concerns of…	Aggravates concerns of…
Exposers 	Internal Validity	

- … subjects tend to change their behavior and responses in the presence of the experimenter … while bots can address that, **design matters** – similar effects if the bot is human-like

Role	Alleviates concerns of…	Aggravates concerns of…
Exposer 	Statistical Validity	

- … **unreliability of treatment implementation** and **extraneous variance** in setting by standardizing the actions taken to expose subjects to treatments

Role	Alleviates concerns of…	Aggravates concerns of…
Subject 	Internal Validity	

- … **regression** and **attrition** by synthesizing, controlling, and normalizing the units receiving and responding to treatments

Role	Alleviates concerns of…	Aggravates concerns of…
Subject 	Construct Validity	

- … **confounding, reactive self-report changes, reactivity to the experiment situation, compensatory equalization and rivalry, resentful demoralization, and treatment diffusion** for the same reasons … but, such issues could remain if the bot is “too human”

Role	Alleviates concerns of…	Aggravates concerns of…
Subject 		Internal Validity

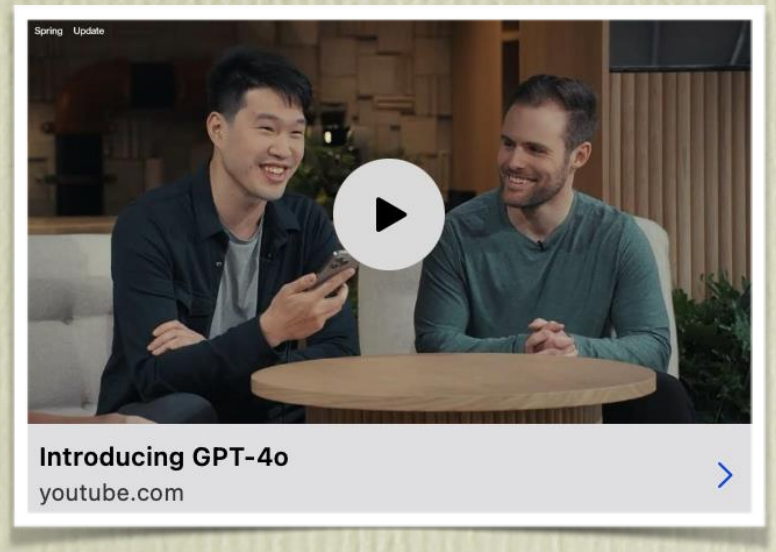
- … taking a test once will influence scores when the test is taken again. **Practice** and **familiarity** could be mistaken for treatment effects

Role	Alleviates concerns of…	Aggravates concerns of…
Subject 		External Validity

- Can we really trust the results of bot experiments to **generalize to human experiments**? … especially given biases in data (e.g., primarily white males) and models, and whether they can reflect real human subpopulations (e.g., Aher et al. 2023, low algorithmic fidelity)

Mitigating Strategies (#1)

- Experiment with **newly developed LLM bots**, which, by nature of training and design, are computational models of humans (Horton 2023)



Mitigating Strategies (#2)

- **Fine-tune LLM bots** for the context of interest before the experiment
  - Horton (2023) endowed bots with a “point of view” to replicate a social preferences experiment

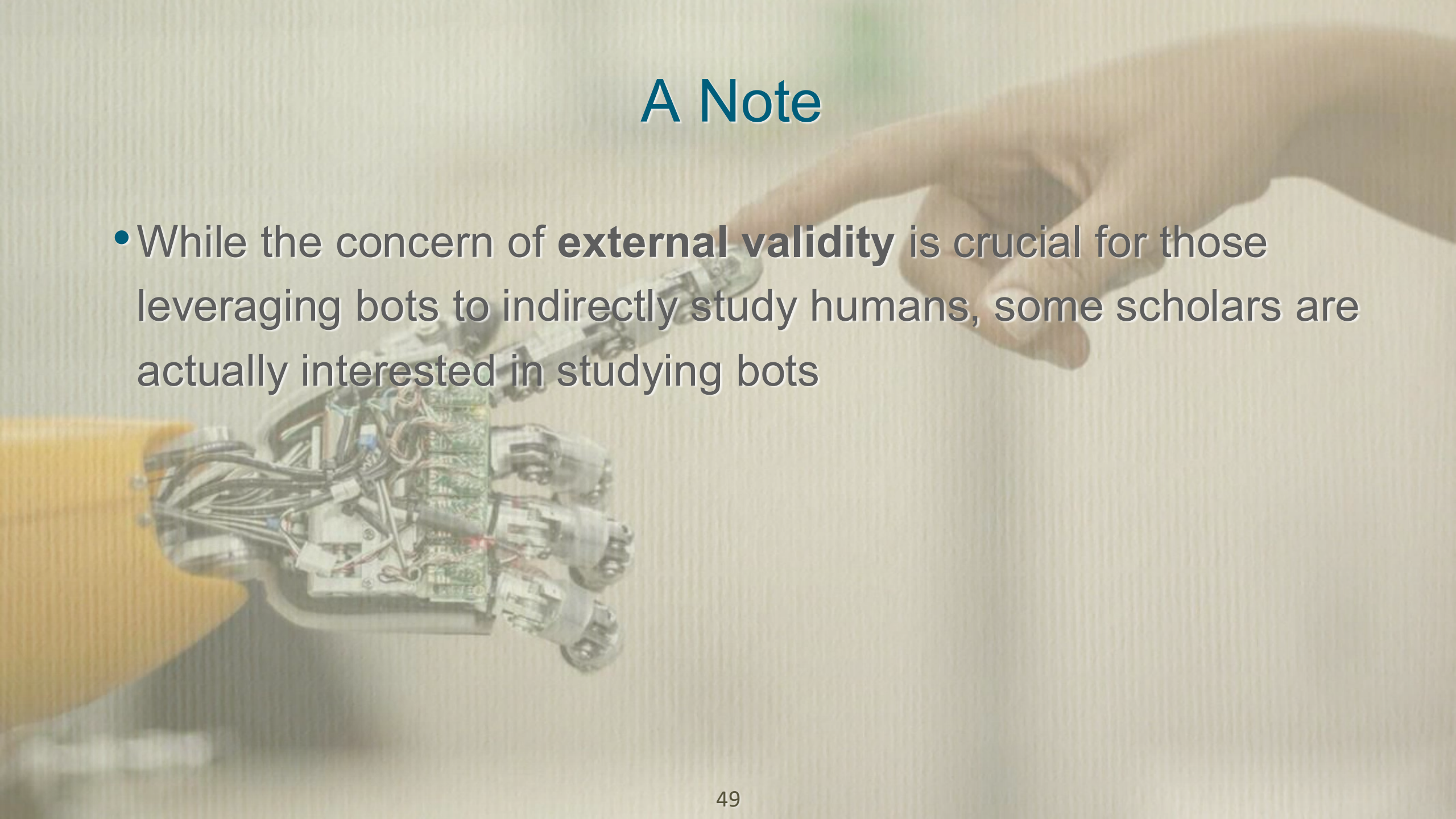
Mitigating Strategies (#3)

- **Perform a set of robustness checks** after the experiment to validate design

#	Robustness Checks
1	Illustrate that bot activity is in line with fine tuning
2	Run the same experiment with different bots and show inconsistencies are due to suitable design choices
3	Compare results against those of prior studies with humans (or even a small new experiment) and show they are qualitatively the same

A Note

- While the concern of **external validity** is crucial for those leveraging bots to indirectly study humans, some scholars are actually interested in studying bots



Designing Bot Experiments

- Bot experiments are already happening
- We can do them well by choosing **roles for bots**, and given these, designing experiments that **minimize validity concerns**

Thank You!

Chatbots: The New Normal? Or Still the Next Thing?

Jason Bennett Thatcher

Tandean Rustandy Esteemed Endowed Chair

Leeds School of Business, University of Colorado Boulder

This is our third conversation about bots in three years?

What has changed?

Bots are now part of the business world

Customer service

Therapy

Confession

If Bots are now normal?
Is this an interesting topic?

Maybe?

How do we keep it real?

How do we keep it real?
and interesting?

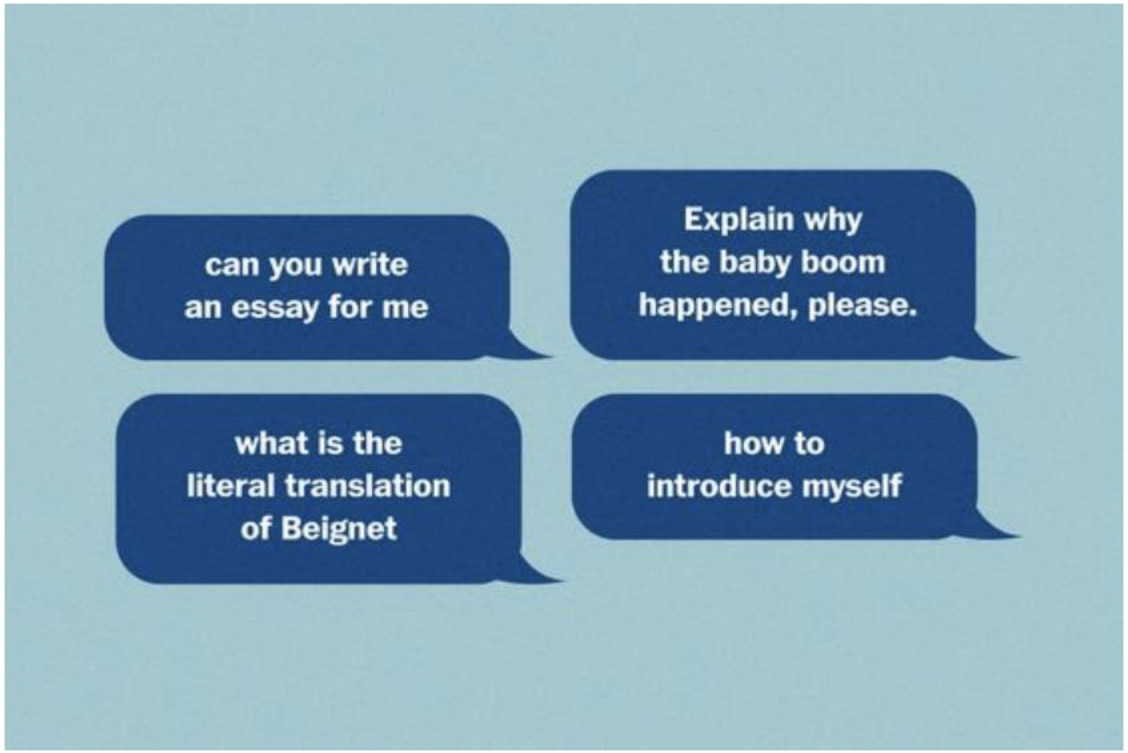
Three opportunities.

Three opportunities.

Opportunity One

Rather than talking about what is coming, we need to talk about what is.

What do people really ask chatbots? It's a lot of sex and homework.



(Queries from WildChat)

AI chatbots are taking the world by storm. We analyzed thousands of conversations to see what people are really asking them and what topics are most discussed.

By Jeremy B. Merrill and Rachel Lerman

We need to study bots as part of every day life.

OPINION

By Stephanie Takyi

My seven years on dating apps has been a cesspit of bots, scammers and weirdos

8 of the Best Stock Trading Bots to Consider in 2024

The best stock trading bots offer various features, including backtesting, control over parameters, and numerous pre-built designs to choose from.

Nkechi Iregbulem, Business Operations Associate, Composer Technologies

Jan 09 2024

Share

Table of Contents

Timing is everything when it comes to making money in the stock market. Milliseconds can make the difference between a winning trade and a loser. Traders increasingly leverage artificial intelligence (AI) and algorithmic trading systems, such as stock trading bots, to gain a competitive edge.

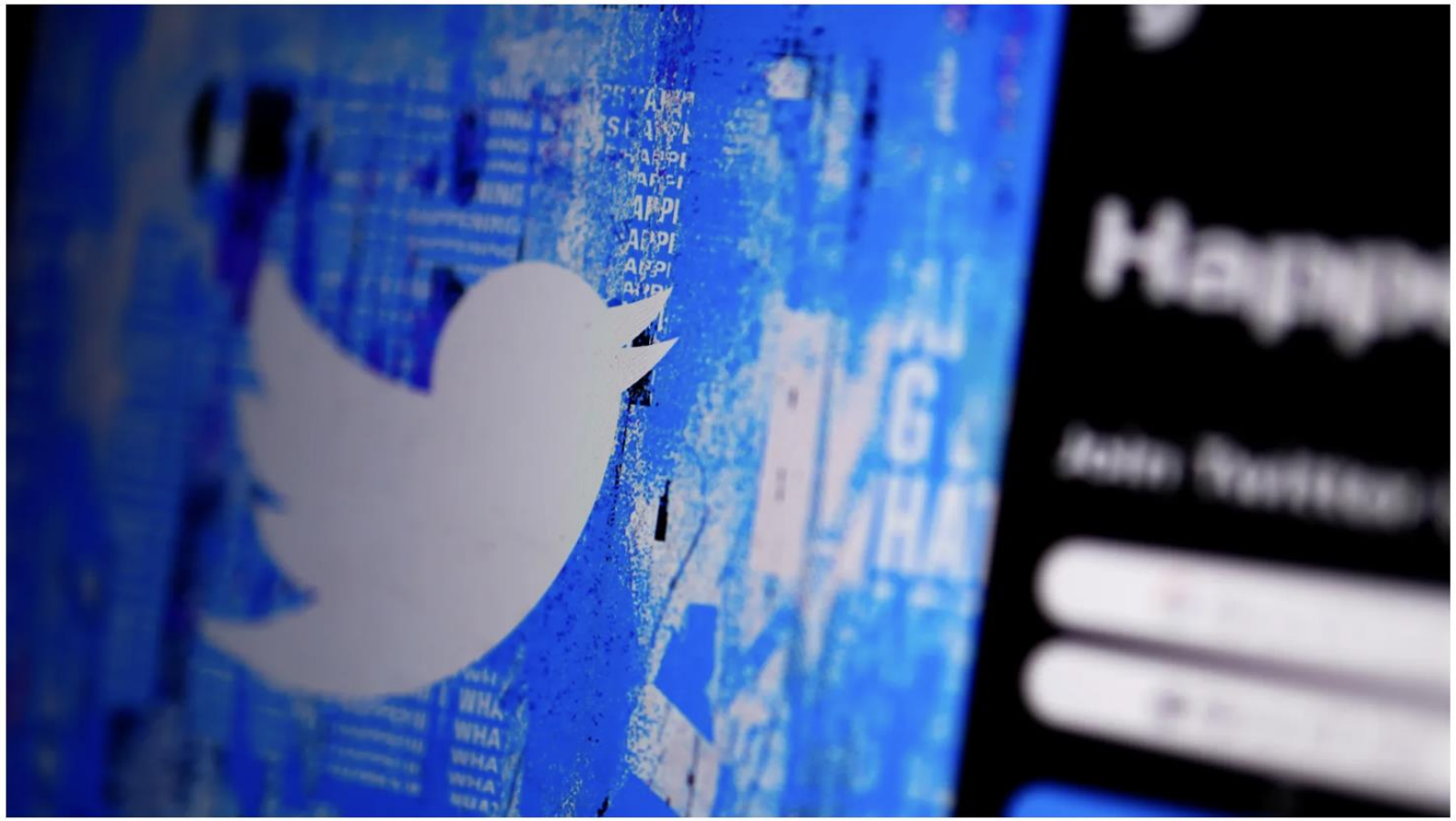
These automated trading systems buy and sell on stock exchanges nearly instantaneously, allowing investors to rapidly leverage any advantage to improve trading performance. Let's explore what a stock trading bot is, the different types, how to choose one, and some of the best trading bots on the market today.

We need to study bots as a
good and bad
part of every day life.

Opportunity Two

We need to ask what shapes perceptions of bots as participants

Thousands of pro-Trump bots are attacking DeSantis, Haley



FILE – The Twitter splash page is seen on a digital device on April 25, 2022, in San Diego. Researchers have uncovered a network of tens of thousands of fake Twitter accounts created to support ex-President Donald Trump and attack his critics and potential rivals. Those targeted by the bot network include Nikki Haley, the former South Carolina governor and U.N. secretary now challenging Trump for the Republican nomination, as well as Florida Gov. Ron DeSantis. (AP Photo/Gregory Bull, File)

Are bots trying to undermine Donald Trump?

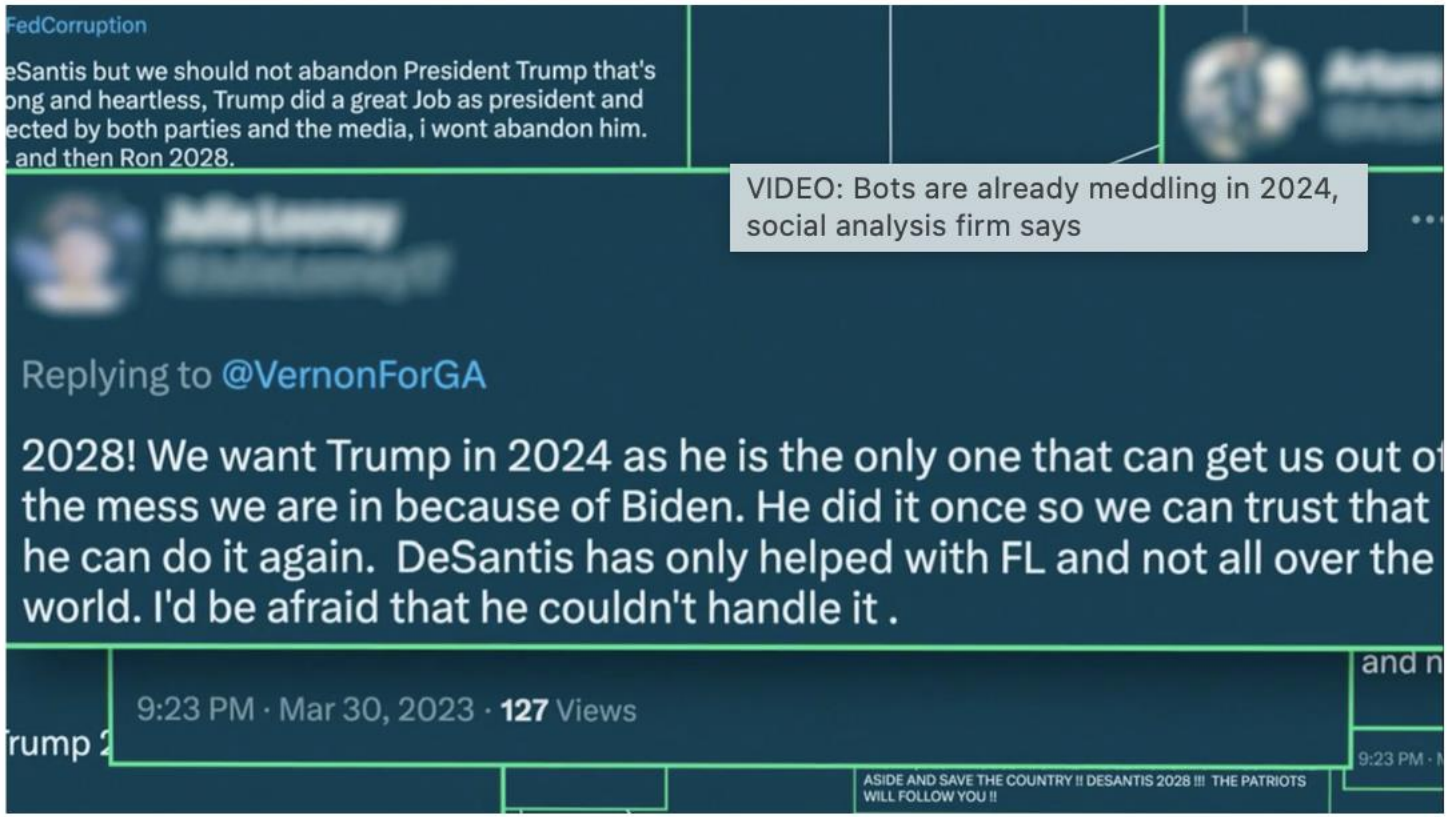
May 09, 2024 | Riley Callanan

Credit: Jess Frampton

How pro-Trump bots are sowing division in the Republican Party: Report

Bots are going after Trump's potential 2024 rivals, a social analysis firm says.

By **Emmanuelle Saliba**
April 13, 2023, 5:41 AM



Bots are already meddling in 2024, social analysis firm says

Thousands of automated Twitter accounts appear to be praising Donald Trump and ridiculing his politic... **Show More**

We need to ask how does the broader context tie to our use and beliefs about bots

And this work needs to go beyond the platform and examine bots as active participants in society

Third Opportunity

Trust and bots

What makes bots trusted partners versus malicious actors

FORBES › INNOVATION › CYBERSECURITY

Top AI Chatbots Spread Russian Propaganda

Emma Woollacott Senior Contributor

Follow

1

Jun 19, 2024, 07:48am EDT

Updated Jun 20, 2024, 07:03am EDT

Fake News GETTY

Disinformation Researchers Raise Alarms About A.I. Chatbots

Researchers used ChatGPT to produce clean, convincing text that repeated conspiracy theories and misleading narratives.

Share full article 183

Alamy

How TikTok bots and AI have powered a resurgence in UK far-right violence

Experts warn growth of extremist influencers and 'micro-donations' could create even bigger wave of unrest

Anti-racism campaigners fear online tools will make it easier for extremist groups to recruit and organise. Photograph: Vuk Valcic/ZUMA Press Wire/Rex/Shutterstock

Bot research needs to join the broader corpus of trust research

Bot research needs to join the broader corpus of trust research and management research in general

Because Bot research is the now normal research and has a bright future in the years to come

Thank you
(jason.thatcher@colorado.edu)

Panel

Hani Safadi
UGA

Anna Priante
RSM

Lior Zalmanson
Tel Aviv University

Jason Thatcher
UC Boulder

Carolina Salge
UGA

Aaron Schecter
UGA

RSM Erasmus | Rotterdam School of Management Erasmus University

Terry College of Business
UNIVERSITY OF GEORGIA

RSM Erasmus | Rotterdam School of Management
Erasmus University

CTO

Thank you!

AoM PDW – Next Decade Bot Research

Terry College of Business
UNIVERSITY OF GEORGIA