Scientific Research: Two Paradigm Shifts?

Noshir Contractor
Jane S. & William J. White Professor of Behavioral Sciences
Northwestern University, USA

&

"Faux-shir" Contractor (aka Gen AI)

@noshir @noshir.bsky.social @Noshir@mastodon.social

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SONIC advancing the science of networks in communities

Two Paradigm Shifts?

Shifts in the **object of scientific inquiry?**

Shifts in the **conduct of scientific inquiry?**

Shifts in the Object of Scientific Inquiry?

SOCIAL SCIENCE

Computational Social Science

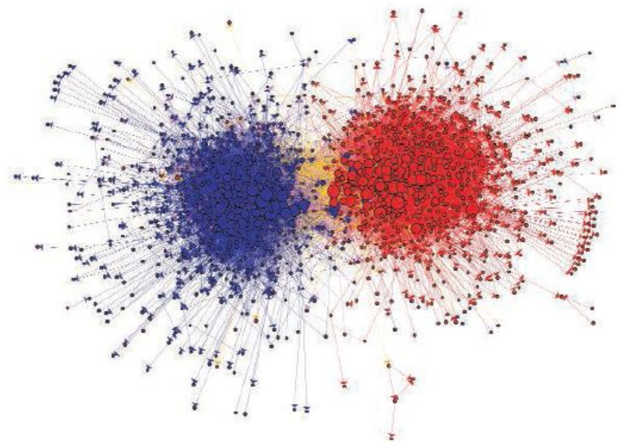
A field is emerging that leverages the capacity to collect and analyze data at a scale that may reveal patterns of individual and group behaviors.

David Lazer,[1] Alex Pentland,[2] Lada Adamic,[3] Sinan Aral,[2,4] Albert-László Barabási,[5] Devon Brewer,[6] Nicholas Christakis,[1] Noshir Contractor,[7] James Fowler,[8] Myron Gutmann,[3] Tony Jebara,[9] Gary King,[1] Michael Macy,[10] Deb Roy,[2] Marshall Van Alstyne[2,11]

We live life in the network. We check our e-mails regularly, make mobile phone calls from almost any location, swipe transit cards to use public transportation, and make purchases with credit cards. Our movements in public places may be captured by video cameras, and our medical records stored as digital files. We may post blog entries accessible to anyone, or maintain friendships through online social networks. Each of these transactions leaves digital traces that can be compiled into comprehensive pictures of both individual and group behavior, with the potential to transform our understanding of our lives, organizations, and societies.

The capacity to collect and analyze massive amounts of data has transformed such fields as biology and physics. But the emergence of a data-driven "computational social science" has been much slower. Leading journals in economics, sociology, and political science show little evidence of this field. But computational social science is occurring—in Internet companies such as Google and Yahoo, and in government agencies such as the U.S. National Security Agency. Computational social science could become the exclusive domain of private companies and government agencies. Alternatively, there might emerge a privileged set of academic researchers presiding over private data from which they produce papers that cannot be critiqued or replicated. Neither scenario will serve the long-term public interest of accumulating, verifying, and disseminating knowledge.

What value might a computational social science—based in an open academic environment—offer society, by enhancing understanding of individuals and collectives? What are the



Data from the blogosphere. Shown is a link structure within a community of political blogs (from 2004), where red nodes indicate conservative blogs, and blue liberal. Orange links go from liberal to conservative, and purple ones from conservative to liberal. The size of each blog reflects the number of other blogs that link to it. [Reproduced from (8) with permission from the Association for Computing Machinery]

[1]Harvard University, Cambridge, MA, USA. [2]Massachusetts Institute of Technology, Cambridge, MA, USA. [3]University of Michigan, Ann Arbor, MI, USA. [4]New York University, New York, NY, USA. [5]Northeastern University, Boston, MA, USA. [6]Interdisciplinary Scientific Research, Seattle, WA, USA. [7]Northwestern University, Evanston, IL, USA. [8]University of California–San Diego, La Jolla, CA, USA. [9]Columbia University, New York, NY, USA [10]Cornell University, Ithaca, NY, USA. [11]Boston University, Boston, MA, USA. E-mail: david_lazer@harvard.edu. Complete affiliations are listed in the supporting online material.

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Northwestern University

SONIC advancing the science of networks in communities

Perspective

Measuring algorithmically infused societies

https://doi.org/10.1038/s41586-021-03666-1

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Check for updates

Claudia Wagner[1,2,3]✉, Markus Strohmaier[1,2,3], Alexandra Olteanu[4,5], Emre Kıcıman[6], Noshir Contractor[7] & Tina Eliassi-Rad[8]

It has been the historic responsibility of the social sciences to investigate human societies. Fulfilling this responsibility requires social theories, measurement models and social data. Most existing theories and measurement models in the social sciences were not developed with the deep societal reach of algorithms in mind. The

POLICY FORUM

SOCIAL SCIENCE

Computational social science: Obstacles and opportunities

Data sharing, research ethics, and incentives must improve

By David M. J. Lazer[1,2], Alex Pentland[3], Duncan J. Watts[4], Sinan Aral[3], Susan Athey[5], Noshir Contractor[6], Deen Freelon[7], Sandra Gonzalez-Bailon[4], Gary King[2], Helen Margetts[8,9], Alondra Nelson[10,11], Matthew J. Salganik[12], Markus Strohmaier[13,14], Alessandro Vespignani[1], Claudia Wagner[14,15]

dependencies within data. A loosely connected intellectual community of social scientists, computer scientists, statistical physicists, and others has coalesced under this umbrella phrase.

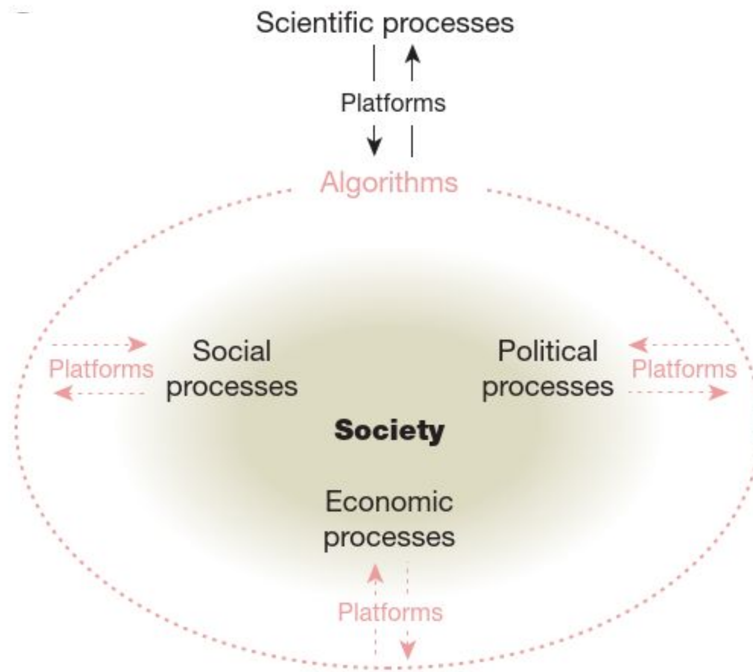
MISALIGNMENT OF UNIVERSITIES

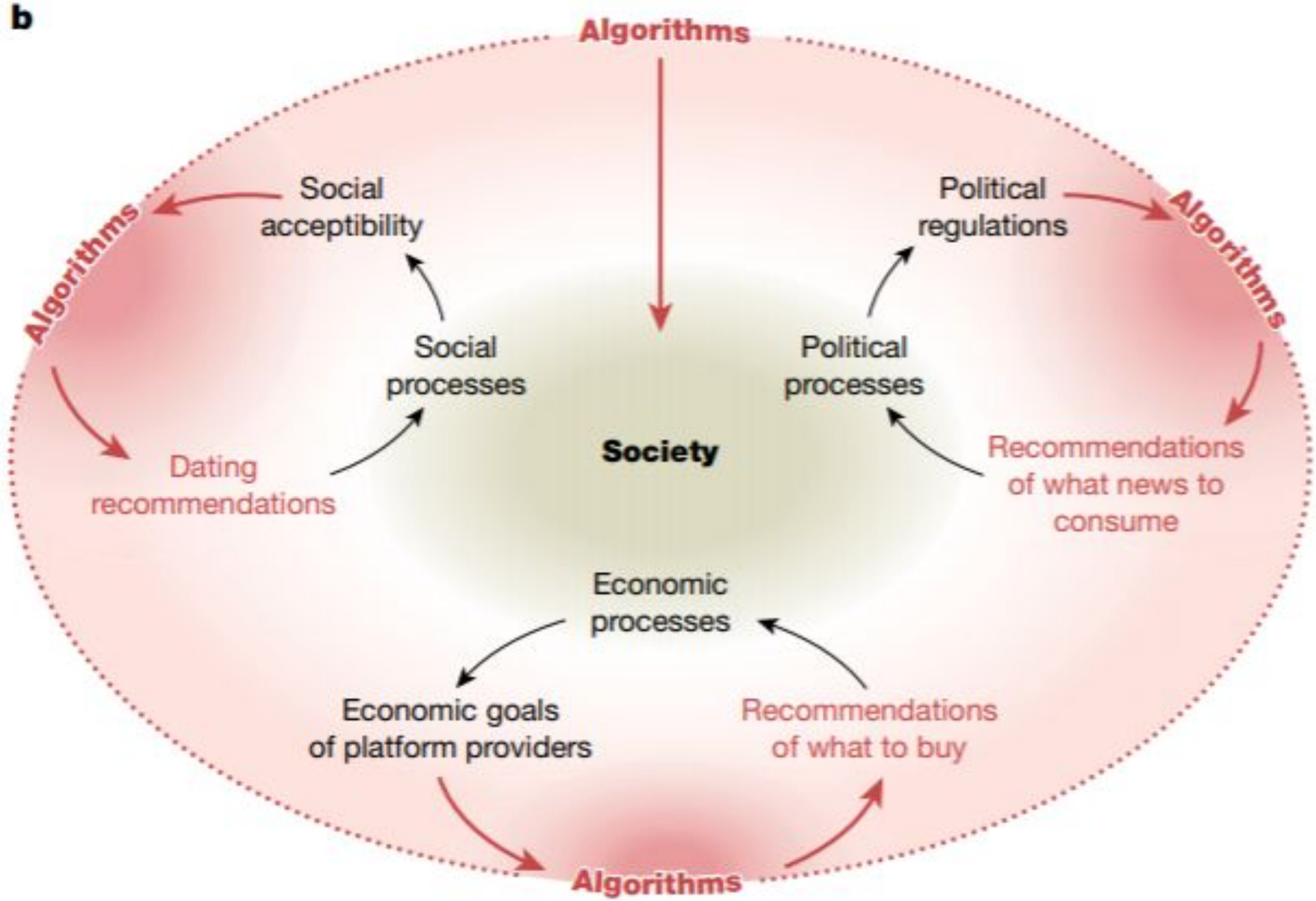
Wagner, C., Strohmaier, M., Olteanu, A., Kıcıman, E., Contractor, N., & Eliassi-Rad, T. (2021). Measuring algorithmically infused societies. *Nature*, *595*(7866), 197–204.

Lazer, D. M. J., Pentland, A., Watts, D. J., Aral, S., Athey, S., Contractor, N., Freelon, D., Gonzalez-Bailon, S., King, G., Margetts, H., Nelson, A., Salganik, M. J., Strohmaier, M., Vespignani, A., & Wagner, C. (2020). Computational social science: Obstacles and opportunities. *Science*, *369*(6507), 1060–1062.

The subject of investigation has changed for social scientists.

We witness the emergence of algorithmically infused societies.

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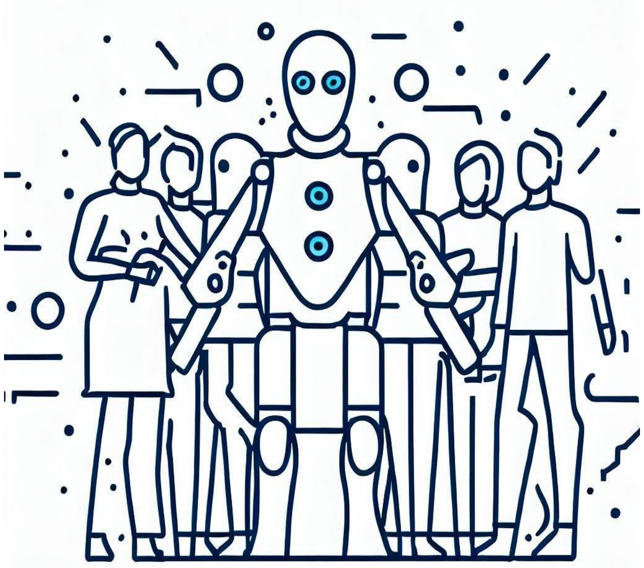
Economic goals
of platform providers
Recommendations
of what to buy
Algorithms

Human-AI Teaming

Human-AI teams **can** capitalize on the best of human and machine intelligence

Synergy viewpoint: AI **can** augment human capabilities and interactions within a team



Bing Image Creator – AI augment human in line art style

Background

Bing Image Creator – Boeing 737-MAX
in line art style

Process loss: AI **can** interfere with and degrade needed team states among human members

Background

Bing Image Creator – Radiologist looks at X-Ray results in line art style

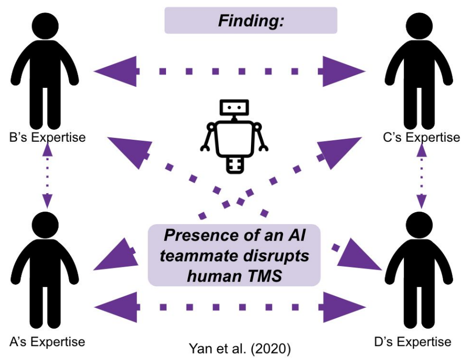
Process loss: AI **can** interfere with and degrade needed team states among human members

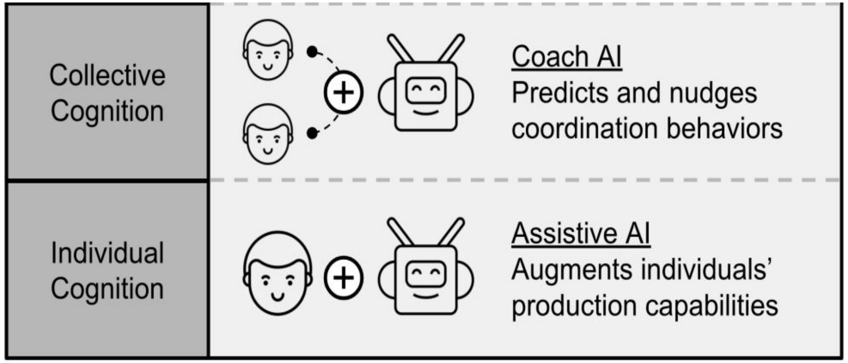
“unless the documented mistakes can be corrected, the optimal solution involves assigning cases either to humans or to AI, but **rarely to a human assisted by AI**.”

Agarwal, N., Moehring, A., Rajpurkar, P., & Salz, T. (2023). Combining Human Expertise with Artificial Intelligence: Experimental Evidence from Radiology (No. w31422). *National Bureau of Economic Research*.

Toward **E**nhanced **A**daptive **M**achine **S**ynergies
T.E.A.M.S.

Prior research demonstrates the potential for process loss, hence the need to design AI, and nudge humans, toward successful coordination





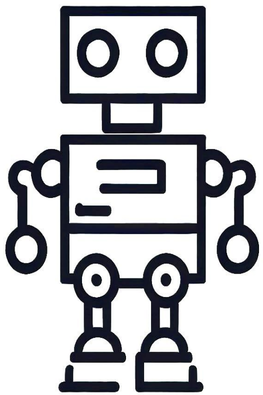
Yan, B., Lewis, K., Figge, P., Hollingshead, A., Steves Alexander, K., Kim, Y. J., & Fang, C. (2020). Intelligent Machines and Teamwork: Help or Hindrance?. *Academy of Management Proceedings* (Vol. 2020, No. 1, p. 21962).
Gupta, P., & Woolley, A. W. (2021, September). Articulating the role of artificial intelligence in collective intelligence: A transactive systems framework. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 65, No. 1, pp. 670-674).

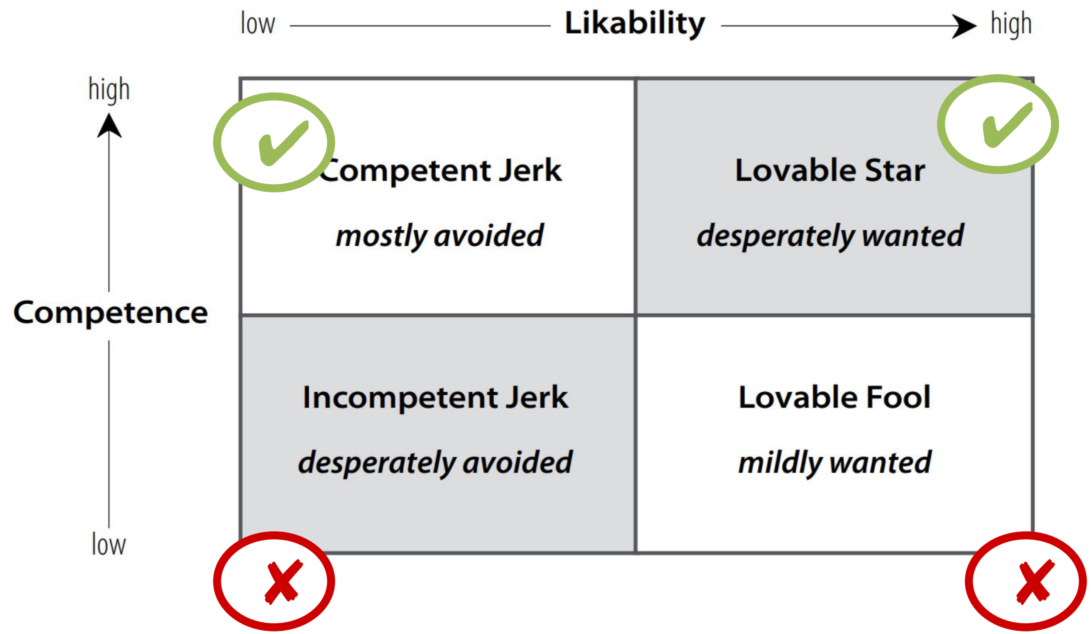
Finding #1

Simulated AI that performs **taskwork** is more beneficial than AI that helps regulate **teamwork**

In contrast to perceptions of human teammates, where teamwork contributions are equally valued and augment the value of taskwork, human teams expect AI to contribute to taskwork

Finding #2





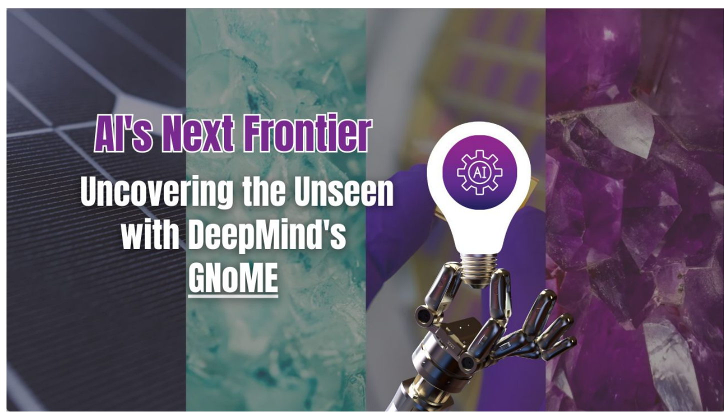
Humans prioritize **competence** over warmth in AI teammates.

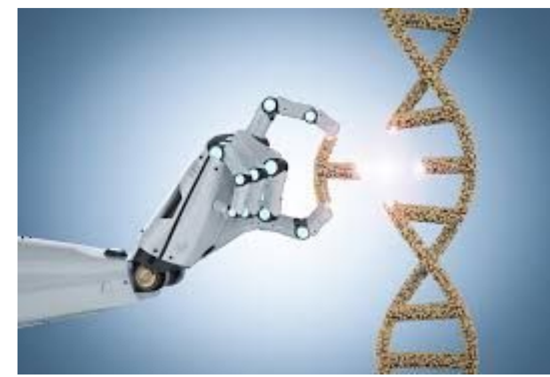
Casciaro, T., & Lobo, M. S. (2005). Competent jerks, lovable fools, and the formation of social networks. Harvard business review, 83(6), 92-99.

Two Paradigm Shifts?

Shifts in the **object of scientific inquiry?**

Shifts in the **conduct of scientific inquiry?**





Shifts in the Object of Scientific Inquiry?

Lessons from Forecasting Technology

- Utopian
- Dystopian
- Neutral
- Contingency - Dual Effects
  - Telephone

Lessons on Stages of Technology Use

Substitution

Substitution

- Adoption based on relative advantage, observability, adaptability, compatibility, trialability

- Examples: Automobiles, Telephone, Videoconferencing, Arpanet/Internet, WWW

Dawn of Gen AI

MISTRAL AI_ 7

ChatGPT

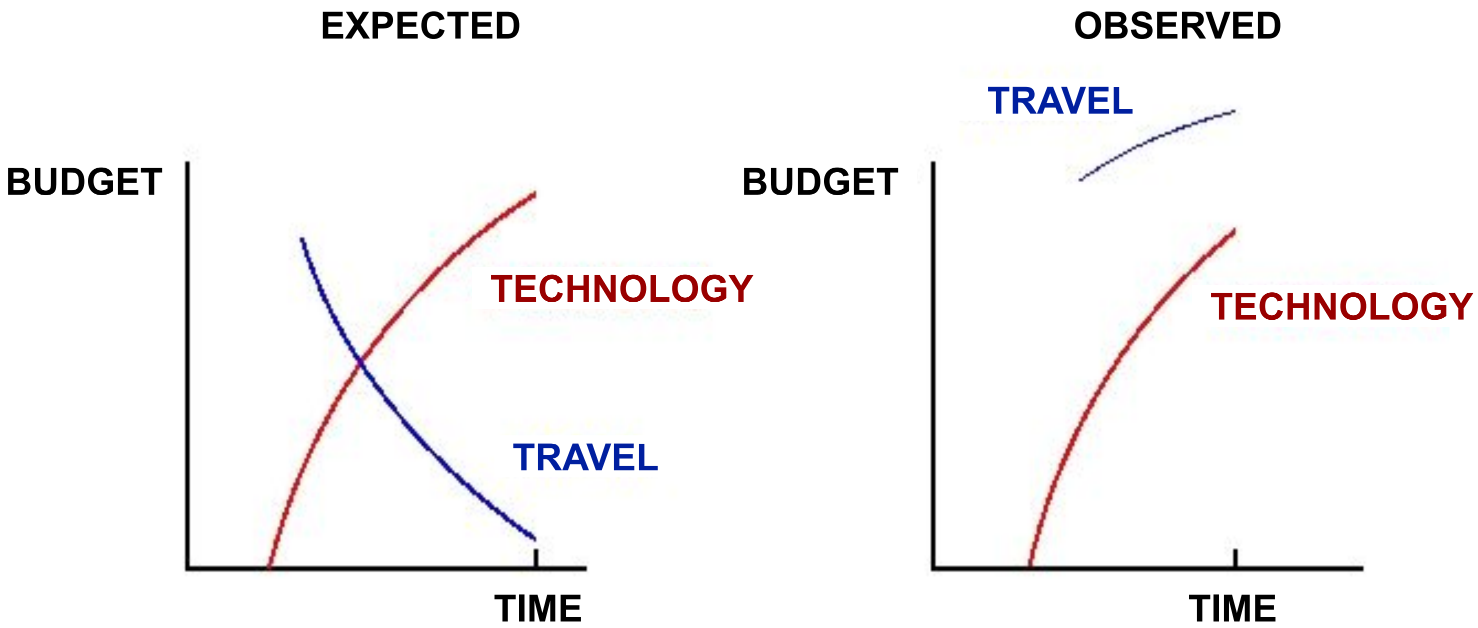
Claude

BY ANTHROP\C

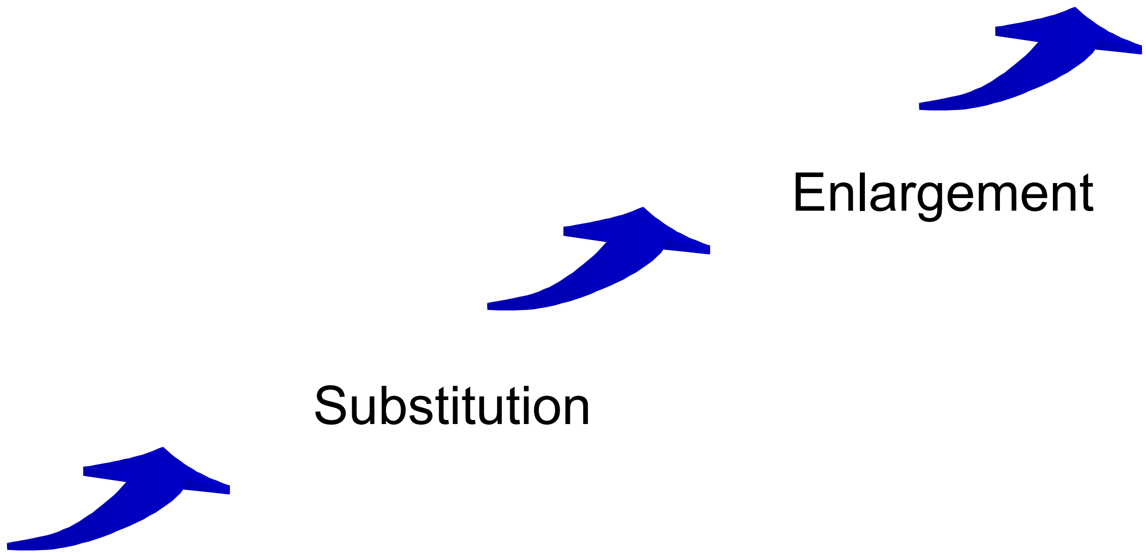
perplexity

Substitution Effects

Telecommunications Transportation Tradeoff



Stages of Technology Use



Time to reach a quarter of the US population

- 1873, Electricity: 46 yrs.
- 1876/Telephone: 35 yrs.
- 1886/Automobile: 55 yrs.
- 1906/Radio: 22 yrs.
- 1926, TV: 26 yrs.

- 1953/Microwave: 30 yrs.
- 1975/PC: 16 yrs.
- 1983/Mobile phone: 13 yrs.
- 1989/Web: 7 yrs.
- 2009/ Facebook 5 yrs.
- 2020/ TikTok 3 yrs.

ChatGPT reaches 100 million users two months after launch

Unprecedented take-up may make AI chatbot the fastest-growing consumer internet app ever, analysts say

ChatGPT is owned by Microsoft-backed company OpenAI. Photograph: Pavlo Gonchar/Sopa Images/Rex/Shutterstock

Enlargement

- **Moore's Law**: Computational power doubles every 18 months
- **Metcalfe's Law**: The value of a network is proportional to the number of users squared
- **Think Exponential:**

  Human beings have trouble thinking in exponentials. If you have one adopter of an app and users double every three days …..

  *After 30 days you have about a **thousand** adopters.*

  *But you go 30 days longer. Now you have a **million** adopters.*

  *Then you wait another 30 days. Now you have a **billion** adopters!*

Enlargement

- Current 32 bit IP addresses can accommodate 4295 million devices
- The new proposed 132 bit IP address scheme can accommodate (340 followed by 36 zeros or 340 undecillion) devices
- WELCOME to the INTERNET oF THINGS (IoT)

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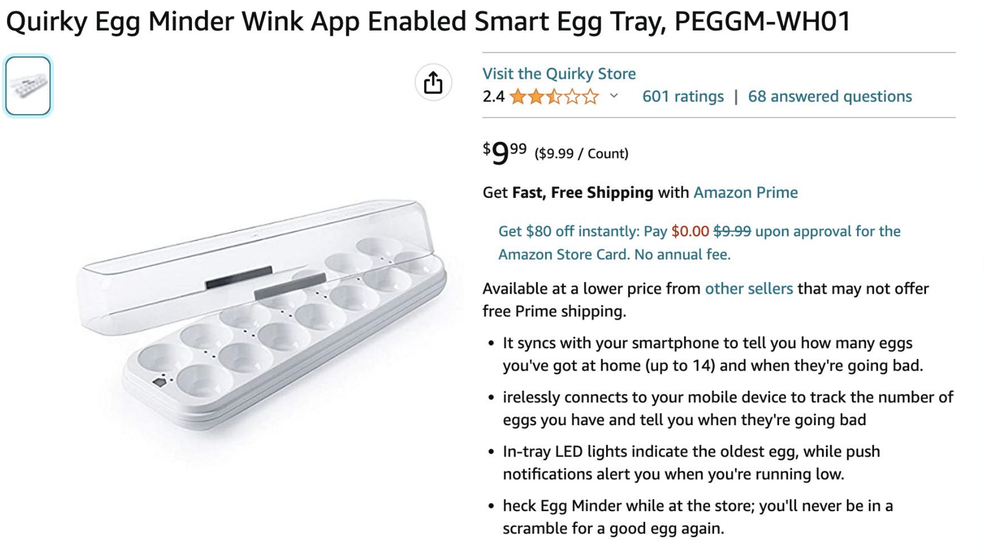
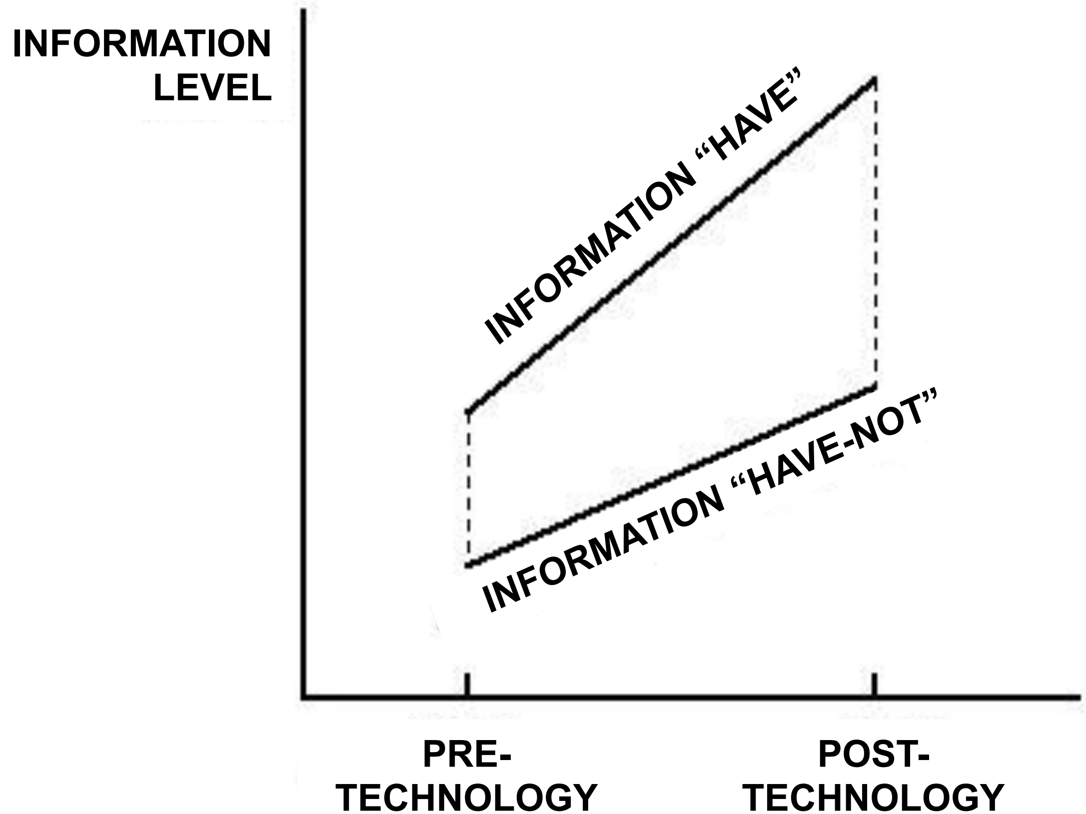


Enlargement: Information Gap

- Emerging technologies improve the amount of information among the “haves” and the “have-nots”
- But the “haves” are much better informed than the “have-nots” resulting in an increase in the Information Gap

Information Gap Hypothesis

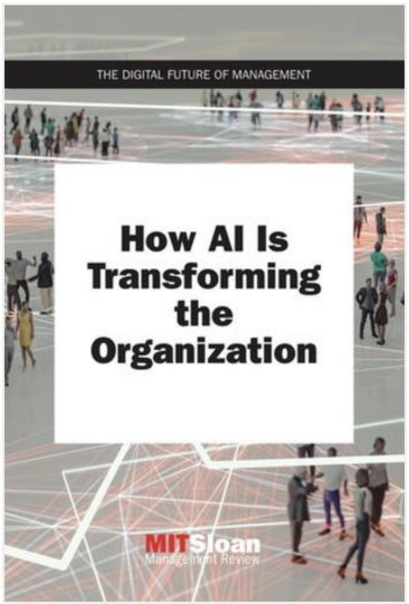


Productivity Paradox

Nobel Prize-winning economist Robert Solow famously observed, "***You can see the computer age everywhere but in the productivity statistics***," an idea that came to be known as the productivity paradox

- This paradox is also known as the Solow paradox.

AI-Productivity Paradox



10: Unpacking the AI–Productivity Paradox

By Erik Brynjolfsson , Daniel Rock , Chad Syverson

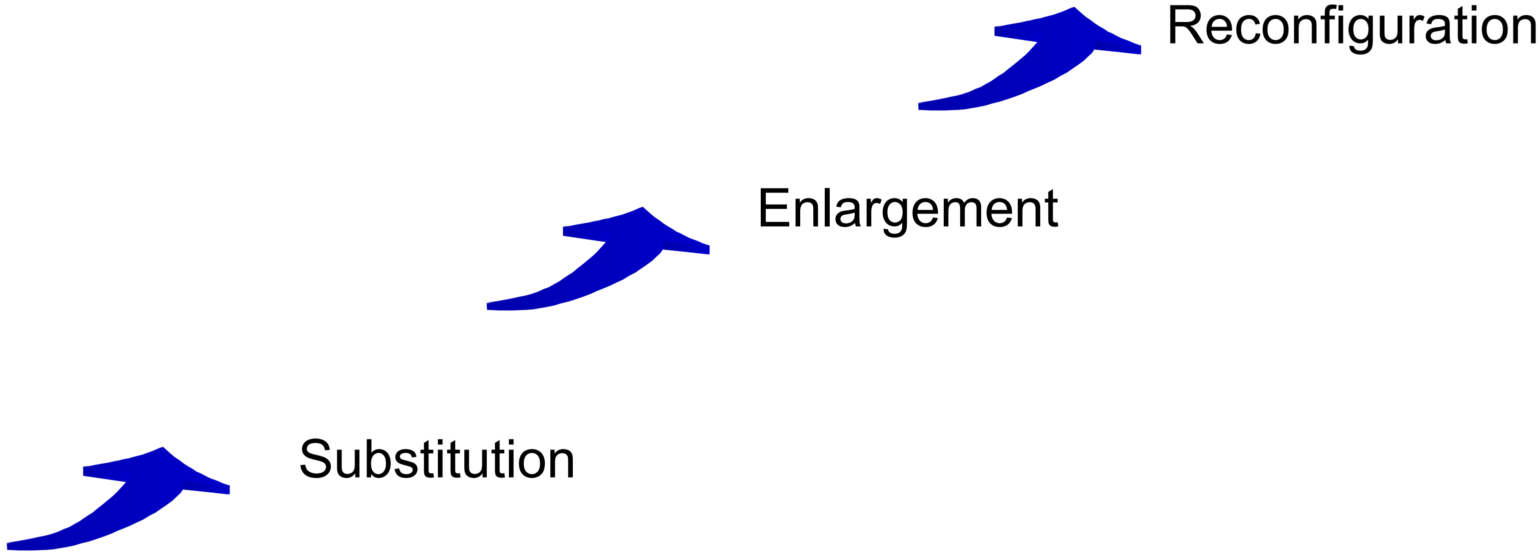
DOI: https://doi.org/10.7551/mitpress/12588.003.0014

Published: 2020

We see the effects of transformative new technologies **everywhere except in productivity statistics**. Systems using artificial intelligence (AI) increasingly match or surpass human-level performance, driving great expectations and soaring stock prices. Yet measured productivity growth has declined …

Past surges in productivity were driven by **general-purpose technologies (GPTs) like electricity and the internal combustion engine**. In turn, these technologies required numerous complementary co-inventions like factory redesigns, interstate highways, new business processes, and changing workforce skills before they truly fulfilled their potential.

Stages of Technology Use



Reconfiguration Effects

- Automobile: H-way

- Arpanet/Internet: I-way

- WWW & IP devices: IoT

Reconfiguration Effects

***Amara's Rule** (1925–2007 American futurologist):*

We overestimate the effect of technology in the short term and underestimate it in the long term.

Stages of Use of AI in Research: Clerk, Colleague, & Coach (Andrew McAfee)

Reconfiguration

Enlargement

Substitution

AI in Research Design & Experiments

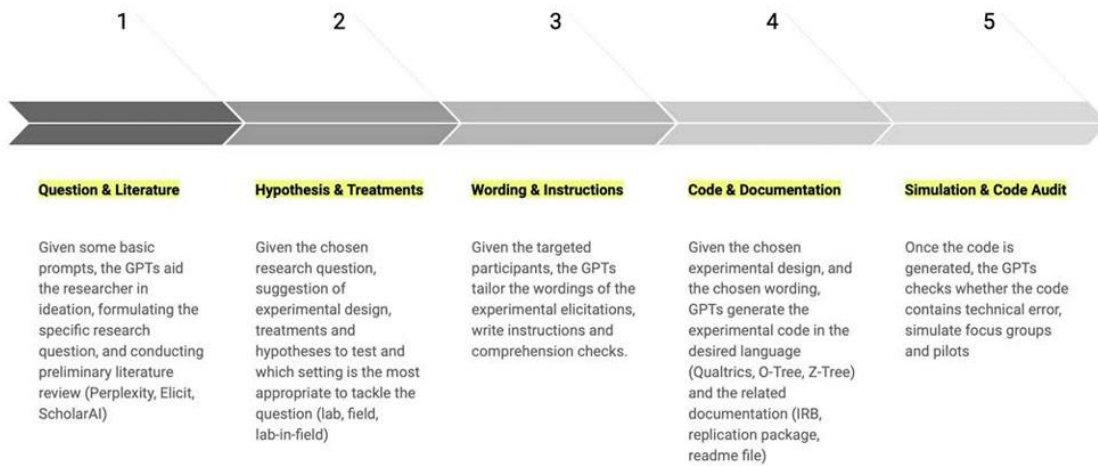


Figure 1: AI can help in the 5 different phases of design

Charness, G., Jabarian, B., & List, J. A. (2023). GENERATION NEXT: EXPERIMENTATION WITH AI.

https://www.nber.org/system/files/working_papers/w31679/w31679.pdf

AI in Hypothesis Generation

Can ChatGPT be used to generate scientific hypotheses?

Yang Jeong Park, Daniel Kaplan, Zhichu Ren, Chia-Wei Hsu, Changhao Li, Haowei Xu, Sipei Li, Ju Li

…. investigate whether large language models can perform the creative hypothesis generation that human researchers regularly do. **While the error rate is high**, generative AI seems to be able to effectively structure vast amounts of scientific knowledge and provide interesting and testable hypotheses. The future scientific enterprise may include synergistic efforts with **a swarm of "hypothesis machines" , challenged by automated experimentation and adversarial peer reviews.**

AI in Hypothesis Generation

Stanford SOCIAL INNOVATION Review

The Case for Causal AI

Using artificial intelligence to predict behavior can lead to devastating policy mistakes. Health and development programs must learn to apply causal models that better explain why people behave the way they do to help identify the most effective levers for change. *Open access to this article is made possible by Surgo Foundation.*

CITE SHARE COMMENT DOWNLOAD PRINT ORDER REPRINTS

By Sema K. Sgaier, Vincent Huang & Grace Charles | Summer 2020

AI in Hypothesis Generation

Humanities & Social Sciences Communications

ARTICLE

Check for updates

https://doi.org/10.1057/s41599-024-03407-5 OPEN

Automating psychological hypothesis generation with AI: when large language models meet causal graph

Song Tong[1,2,3,4,6], Kai Mao[5,6], Zhen Huang[2], Yukun Zhao[2] ✉ & Kaiping Peng[1,2,3,4] ✉

"… analyzed 43,312 psychology articles using a LLM to extract causal relation pairs. This analysis produced a specialized causal graph for psychology. Applying link prediction algorithms, we generated 130 potential psychological hypotheses focusing on "wellbeing", then compared them against research ideas conceived by doctoral scholars and those produced solely by the LLM. Interestingly, our combined approach of a LLM and causal graphs mirrored the expert-level insights in terms of novelty, clearly surpassing the LLM-only hypotheses…"

AI in Research Design & Experiments

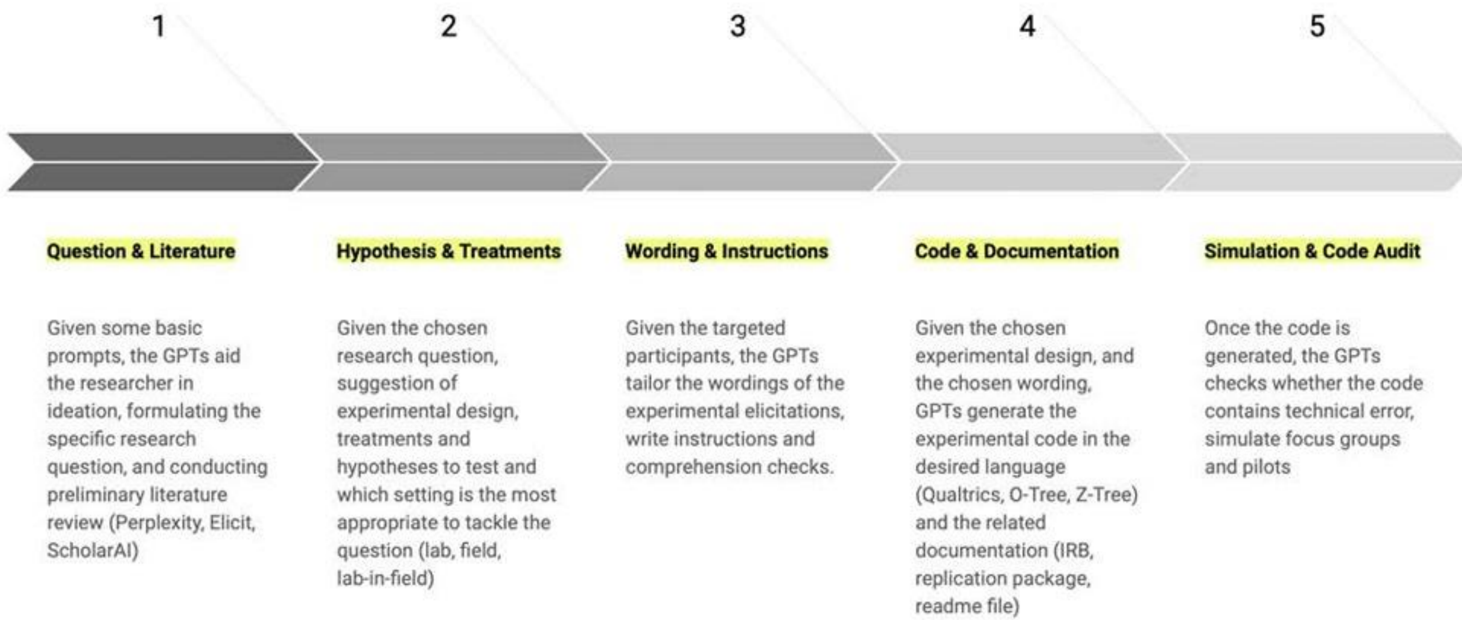


Figure 1: AI can help in the 5 different phases of design

Charness, G., Jabarian, B., & List, J. A. (2023). GENERATION NEXT: EXPERIMENTATION WITH AI. https://www.nber.org/system/files/working_papers/w31679/w31679.pdf

AI-Enhanced Data Collection

Automated Software Engineering (2024) 31:13
https://doi.org/10.1007/s10515-023-00409-6

Check for updates

Can AI serve as a substitute for human subjects in software engineering research?

Marco Gerosa[1] · Bianca Trinkenreich[2] · Igor Steinmacher[1] · Anita Sarma[2]

Received: 13 November 2023 / Accepted: 10 December 2023 / Published online: 11 January 2024

Abstract
Research within sociotechnical domains, such as software engineering, fundamentally requires the human perspective. Nevertheless, traditional qualitative data collection methods suffer from difficulties in participant recruitment, scaling, and labor intensity. This vision paper proposes a novel approach to qualitative data collection in software engineering research by harnessing the capabilities of artificial intelligence (AI), especially large language models (LLMs) like ChatGPT and multimodal foundation models. We explore the potential of AI-generated synthetic text as an alternative source of qualitative data, discussing how LLMs can replicate human responses and behaviors in research settings. We discuss AI applications in emulating humans in interviews, focus groups, surveys, observational studies, and user evaluations. We discuss open problems and research opportunities to implement this vision. In the future, an integrated approach where both AI and human-generated data coexist will likely yield the most effective outcomes.

AI-Enhanced Data Collection

Can AI Replace Human Subjects? A Large-Scale Replication of Psychological Experiments with LLMs

Ziyan Cui[1], cuizy21@mails.tsinghua.edu.cn

Ning Li[1], lining@sem.tsinghua.edu.cn

Huaikang Zhou[1], zhouhk@sem.tsinghua.edu.cn

[1] Tsinghua University, School of Economics and Management

A large-scale study replicated 154 psychological experiments using GPT-4 as a simulated participant. The findings indicate that GPT-4 successfully replicated 76% of main effects and 47% of interaction effects observed in the original studies, suggesting that LLMs can mirror human responses in certain experimental contexts.

AI-Enhanced Data Collection

Demonstrations of the Potential of AI-based Political Issue Polling

Nathan E. Sanders, Alex Ulinich, Bruce Schneier

… developed a prompt engineering methodology for **eliciting human-like survey responses from ChatGPT**, which simulate the response to a policy question of a person described by a set of demographic factors, and produce both an ordinal numeric response score and a textual justification.

… execute large scale experiments, **querying for thousands of simulated responses at a cost far lower than human surveys**

… compare simulated data to human issue polling data from the Cooperative Election Study (CES)

… **ChatGPT is effective at anticipating both the mean level and distribution of public opinion on a variety of policy issues such as abortion bans and approval of the US Supreme Court**, particularly in their ideological breakdown (correlation typically >85%).

…. However, it is l**ess successful at anticipating demographic-level differences**. Moreover, ChatGPT tends to overgeneralize to new policy issues that arose after its training data was collected, such as US support for involvement in the war in Ukraine.

AI-Enhanced Data Collection

Syntheticusers

- Simulating the Human in HCD with ChatGPT: Redesigning Interaction Design with AI
- Embracing naturalistic paradigms: substituting GPT predictions for human judgments
- The Fill-Mask Association Test (FMAT): Measuring Propositions in Natural Language
- Revealing Fine-Grained Values and Opinions in Large Language Models
- Applications of GPT in Political Science Research
- Large Language Models as Simulated Economic Agents: What Can We Learn from Homo Silicus?
- Virtual Personas for Language Models via an Anthology of Backstories
- Using Large Language Models to Simulate Multiple Humans and Replicate Human Subject Studies
- Estimating the Personality of White-Box Language Models

- Evaluating and Inducing Personality in Pre-trained Language Models
- Generating personas using LLMs and assessing their viability
- Identifying and Manipulating the Personality Traits of Language Models
- In-Context Impersonation Reveals Large Language Models' Strengths and Biases
- LLM-Augmented Agent-Based Modelling for Social Simulations: Challenges and Opportunities
- 30 Years of Synthetic Data
- Beyond Demographics: Aligning Role-playing LLM-based Agents Using Human Belief Networks
- Assessing Common Ground through Language-based Cultural Consensus in Humans and Large Language Models
- InsightLens: Discovering and Exploring Insights from Conversational Contexts in Large-Language-Model-Powered Data Analysis
- PATIENT-Ψ: Using Large Language Models to Simulate Patients for Training Mental Health Professionals

AI as Manuscript Reviewer

The AI Review Lottery: Widespread AI-Assisted Peer Reviews Boost Paper Scores and Acceptance Rates

Giuseppe Russo Latona, Manoel Horta Ribeiro, Tim R. Davidson, Veniamin Veselovsky, Robert West

A study analyzing the 2024 International Conference on Learning Representations (ICLR) found that approximately 15.8% of peer reviews were AI-assisted. The research indicated that AI-assisted reviews tended to assign higher scores, potentially influencing acceptance rates

AI as Meta Reviewer

Prompting LLMs to Compose Meta-Review Drafts from Peer-Review Narratives of Scholarly Manuscripts

Shubhra Kanti Karmaker Santu, Sanjeev Kumar Sinha, Naman Bansal, Alex Knipper, Souvika Sarkar, John Salvador, Yash Mahajan, Sri Guttikonda, Mousumi Akter, Matthew Freestone, Matthew C. Williams Jr

One of the most important yet onerous tasks in the academic peer-reviewing process is composing meta-reviews, which involves understanding the core contributions, strengths, and weaknesses of a scholarly manuscript based on peer-review narratives from multiple experts and then summarizing those multiple experts' perspectives into a concise holistic overview. Given the latest major developments in generative AI, especially Large Language Models (LLMs), it is very compelling to rigorously study the utility of LLMs in generating such meta-reviews in an academic peer-review setting. In this paper, we perform a case study with three popular LLMs, i.e., GPT-3.5, LLaMA2, and PaLM2, to automatically generate meta-reviews by prompting them with different types/levels of prompts based on the recently proposed TELeR taxonomy. Finally, we perform a detailed qualitative study of the meta-reviews generated by the LLMs and summarize our findings and recommendations for prompting LLMs for this complex task.

AI and Journal Policies

July 27, 2023

Guidance for Authors, Peer Reviewers, and Editors on Use of AI, Language Models, and Chatbots

Annette Flanagin, RN, MA[1]; Jacob Kendall-Taylor, BA[1]; Kirsten Bibbins-Domingo, PhD, MD, MAS[1]

» Author Affiliations | Article Information

JAMA. 2023;330(8):702-703. doi:10.1001/jama.2023.12500

JAMA and the JAMA Network journals released guidance on the responsible use of these tools by authors and researchers in scholarly publishing.These policies **preclude the inclusion of nonhuman AI tools as authors and require the transparent reporting of use of such tools in preparing manuscripts and other content and when used in research submitted for publication**. In addition, **submission and publication of clinical images created by AI tools is discouraged, unless part of formal research design or methods.** In all such cases, authors must take responsibility for the integrity of the content generated by these models and tools.

AI and Journal Policies

Generative artificial intelligence is infiltrating peer review process

Kunming Cheng, Zaijie Sun, Xiaojun Liu, Haiyang Wu & Cheng Li

Critical Care **28**, Article number: 149 (2024) | Cite this article

On June 23, 2023, the **National Institutes of Health (NIH) implemented a ban on the use of online generative AI tools like ChatGPT for analysis and drafting of peer review comments.** The **Australian Research Council (ARC) also prohibited the use of generative AI in peer review.** Concerning journals, the latest recommendations from the **International Committee of Medical Journal Editors (ICMJE) suggest that reviewers should not upload manuscripts to software or other AI technology platforms that cannot guarantee confidentiality**. Reviewers should disclose to the journal whether and how AI technology was used in evaluating manuscripts or drafting reviewer comments. **The journal *Science* prohibits the use of large language models during peer review and prohibits reviewers from uploading manuscripts to generative AI tools. The *Lancet* maintains that reviewers should refrain from using generative AI or AI-assisted technologies to assist in the scientific review of papers**.

AI and Research Dissemination

Extending Interactive Science Exhibits into the Classroom using Anthropomorphized Chatbots and Bloom's Taxonomy

Yousuf Golding

Virtual Reality for Understanding Artificial-Intelligence-driven Scientific Discovery with an Application in Quantum Optics

Philipp Schmidt, Sören Arlt, Carlos Ruiz-Gonzalez, Xuemei Gu, Carla Rodríguez, Mario Krenn

Simulating Policy Impacts: Developing a Generative Scenario Writing Method to Evaluate the Perceived Effects of Regulation

Julia Barnett, Kimon Kieslich, Nicholas Diakopoulos

AI and Research Dissemination

Simulating Policy Impacts: Developing a Generative Scenario Writing Method to Evaluate the Perceived Effects of Regulation

Julia Barnett, Kimon Kieslich, Nicholas Diakopoulos

… develop a method for using large language models (LLMs) to evaluate the efficacy of a given piece of policy at mitigating specified negative impacts. We do so by using GPT-4 to generate scenarios both pre- and post-introduction of policy and translating these vivid stories into metrics based on human perceptions of impacts. **We leverage an already established taxonomy of impacts of generative AI in the media environment to generate a set of scenario pairs both mitigated and non-mitigated by the transparency policy in Article 50 of the EU AI Act.**

We then run a user study (n =234) to evaluate these scenarios across four risk-assessment dimensions: severity, plausibility, magnitude, and specificity to vulnerable populations. We find that this **transparency legislation is perceived to be effective at mitigating harms in areas such as labor and well-being, but largely ineffective in areas such as social cohesion and security.** Through this case study we demonstrate the efficacy of our method as a tool to iterate on the effectiveness of policy for mitigating various negative impacts

AI and Research Dissemination

From Complexity to Clarity: How AI Enhances Perceptions of Scientists and the Public's Understanding of Science

David M. Markowitz

… by comparing lay summaries of journal articles from PNAS, yoked to those generated by AI

… AI generated significance statements, based on article abstracts, were linguistically simpler than the lay summaries found in the published significance statements

… simply-written GPT summaries facilitated more favorable perceptions of scientists (they were perceived as more credible and trustworthy, but less intelligent) than more complexly-written human PNAS summaries

… participants comprehended scientific writing better after reading simple GPT summaries compared to complex PNAS summaries.

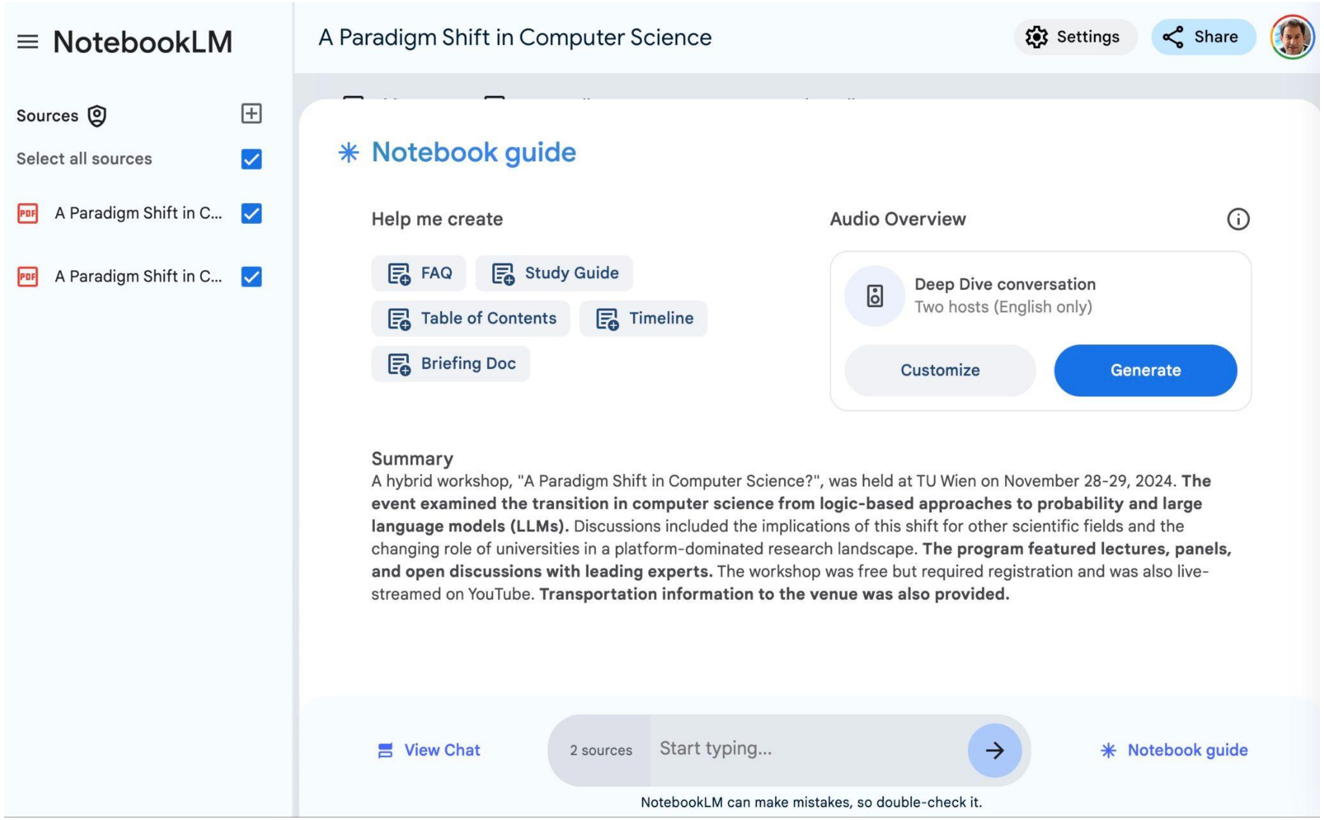
… participants also summarized scientific papers in a more detailed and concrete manner after reading GPT summaries compared to PNAS summaries of the same article

AI and Research Dissemination

- AI-generated video promotions and overview of scholarly events

AI and Research Dissemination

[NotebookLM Demo]



AI in Social Science

PNAS PERSPECTIVE OPEN ACCESS

Can Generative AI improve social science?

Christopher A. Bail[a,b,c,1]

"… potential of Generative AI to improve **survey research, online experiments, automated content analyses, agent-based models**, and other techniques commonly used to study human behavior

… the potential of these tools to perform **literature reviews, identify novel research questions, and facilitate routine research tasks such as writing, data cleaning, and software programming**.

… the many **limitations of Generative AI,** and whether these tools can be deployed by researchers in an **ethical manner** … how **bias in the data used to train these tools** can negatively impact social science research—as well as a range of other challenges related to **internal and external validity, reproducibility, efficiency, and the proliferation of low-quality research**.

…. **highlighting the need for increased collaboration between social scientists and artificial intelligence researchers."**

Bail, C. A. (2024). Can Generative AI improve social science? Proceedings of the National Academy of Sciences of the United States of America, 121(21), e2314021121.

Key Takeaway #1

AI won't replace scientific researchers ……

Researchers with AI will replace researchers without AI.*

**** Adapted from Karim Lakhani, Harvard Business School***

Key Takeaway #2

Collaborative Intelligence

=

AI + AI experts + Domain Experts

Key Takeaway #3

Substitution and Enlargement => Paradigm Glide

Reconfiguration => Paradigm Shift?

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WHERE DISCOVERIES BEGIN

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Science to Shape the Future of the Army
Army Research Office
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