Individual decision lit

Thomas E. Gorman

2024-09-30

## (Ir)rationality and cognitive biases in large language models.

Macmillan-Scott, O., & Musolesi, M. (2024). **(Ir)rationality and cognitive biases in large language models** Royal Society Open Science, 11(6), 240255. https://doi.org/10.1098/rsos.240255

Abstract

Do large language models (LLMs) display rational reasoning? LLMs have been shown to contain human biases due to the data they have been trained on; whether this is reflected in rational reasoning remains less clear. In this paper, we answer this question by evaluating seven language models using tasks from the cognitive psychology literature. We find that, like humans, LLMs display irrationality in these tasks. However, the way this irrationality is displayed does not reflect that shown by humans. When incorrect answers are given by LLMs to these tasks, they are often incorrect in ways that differ from human-like biases. On top of this, the LLMs reveal an additional layer of irrationality in the significant inconsistency of the responses. Aside from the experimental results, this paper seeks to make a methodological contribution by showing how we can assess and compare different capabilities of these types of models, in this case with respect to rational reasoning.

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Figure 1: Figures from Macmillan-Scott & Musolesi (2024)

## Human-like intuitive behavior and reasoning biases emerged in large language models but disappeared in ChatGPT

Hagendorff, T., Fabi, S., & Kosinski, M. (2023). **Human-like intuitive behavior and reasoning biases emerged in large language models but disappeared in ChatGPT.** Nature Computational Science, 3(10), 833–838. https://doi.org/10.1038/s43588-023-00527-x

Abstract

We design a battery of semantic illusions and cognitive reflection tests, aimed to elicit intuitive yet erroneous responses. We administer these tasks, traditionally used to study reasoning and decision-making in humans, to OpenAI’s generative pre-trained transformer model family. The results show that as the models expand in size and linguistic proficiency they increasingly display human-like intuitive system 1 thinking and associated cognitive errors. This pattern shifts notably with the introduction of ChatGPT models, which tend to respond correctly, avoiding the traps embedded in the tasks. Both ChatGPT-3.5 and 4 utilize the input–output context window to engage in chain-of-thought reasoning, reminiscent of how people use notepads to support their system 2 thinking. Yet, they remain accurate even when prevented from engaging in chain-of-thought reasoning, indicating that their system-1-like next-word generation processes are more accurate than those of older models. Our findings highlight the value of applying psychological methodologies to study large language models, as this can uncover previously undetected emergent characteristics.

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Figure 2: Figures from Hagendorff et al. (2023)

## Using cognitive psychology to understand GPT-3.

Binz, M., & Schulz, E. (2023). **Using cognitive psychology to understand GPT-3.** Proceedings of the National Academy of Sciences, 120(6), e2218523120. https://doi.org/10.1073/pnas.2218523120

Abstract

We study GPT-3, a recent large language model, using tools from cognitive psychology. More specifically, we assess GPT-3’s decision-making, information search, deliberation, and causal reasoning abilities on a battery of canonical experiments from the literature. We find that much of GPT-3’s behavior is impressive: It solves vignette-based tasks similarly or better than human subjects, is able to make decent decisions from descriptions, outperforms humans in a multiarmed bandit task, and shows signatures of model-based reinforcement learning. Yet, we also find that small perturbations to vignette-based tasks can lead GPT-3 vastly astray, that it shows no signatures of directed exploration, and that it fails miserably in a causal reasoning task. Taken together, these results enrich our understanding of current large language models and pave the way for future investigations using tools from cognitive psychology to study increasingly capable and opaque artificial agents.

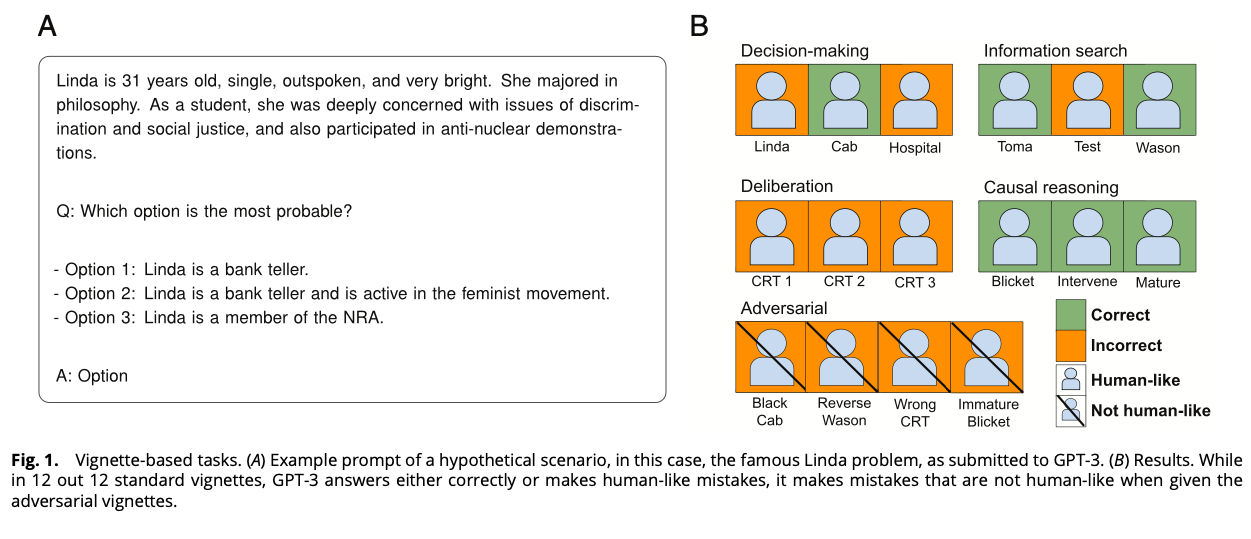


Figure from Binz & Schulz (2023)

## Studying and improving reasoning in humans and machines.

Yax, N., Anlló, H., & Palminteri, S. (2024). **Studying and improving reasoning in humans and machines.** Communications Psychology, 2(1), 1–16. https://doi.org/10.1038/s44271-024-00091-8

Abstract

In the present study, we investigate and compare reasoning in large language models (LLMs) and humans, using a selection of cognitive psychology tools traditionally dedicated to the study of (bounded) rationality. We presented to human participants and an array of pretrained LLMs new variants of classical cognitive experiments, and cross-compared their performances. Our results showed that most of the included models presented reasoning errors akin to those frequently ascribed to error-prone, heuristic-based human reasoning. Notwithstanding this superficial similarity, an in-depth comparison between humans and LLMs indicated important differences with human-like reasoning, with models’ limitations disappearing almost entirely in more recent LLMs’ releases. Moreover, we show that while it is possible to devise strategies to induce better performance, humans and machines are not equally responsive to the same prompting schemes. We conclude by discussing the epistemological implications and challenges of comparing human and machine behavior for both artificial intelligence and cognitive psychology.

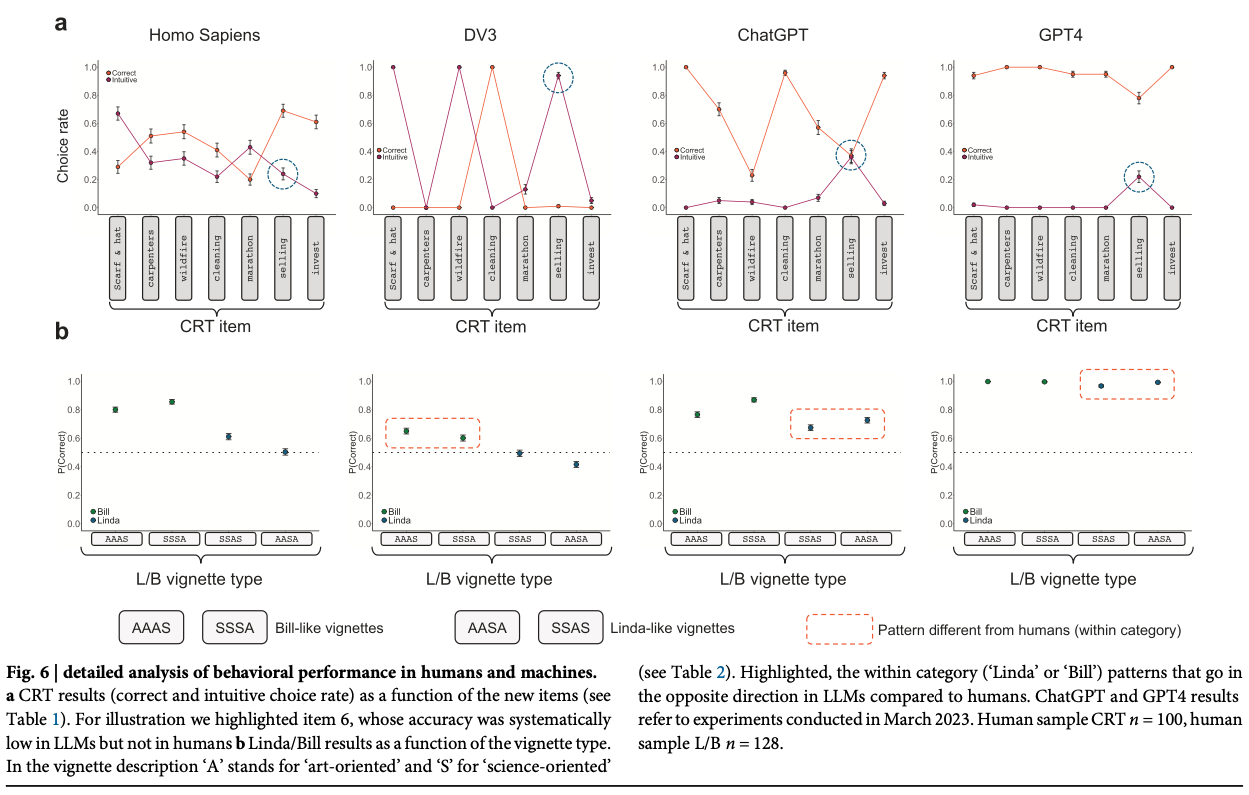


Figure from Yax et al. (2024)

## Exploring variability in risk taking with large language models.

Bhatia, S. (2024). **Exploring variability in risk taking with large language models.** Journal of Experimental Psychology: General, 153(7), 1838–1860. https://doi.org/10.1037/xge0001607

Abstract

What are the sources of individual-level differences in risk taking, and how do they depend on the domain or situation in which the decision is being made? Psychologists currently answer such questions with psychometric methods, which analyze correlations across participant responses in survey data sets. In this article, we analyze the preferences that give rise to these correlations. Our approach uses (a) large language models (LLMs) to quantify everyday risky behaviors in terms of the attributes or reasons that may describe those behaviors, and (b) decision models to map these attributes and reasons onto participant responses. We show that LLM-based decision models can explain observed correlations between behaviors in terms of the reasons different behaviors elicit and explain observed correlations between individuals in terms of the weights different individuals place on reasons, thereby providing a decision theoretic foundation for psychometric findings. Since LLMs can generate quantitative representations for nearly any naturalistic decision, they can be used to make accurate out-of-sample predictions for hundreds of everyday behaviors, predict the reasons why people may or may not want to engage in these behaviors, and interpret these reasons in terms of core psychological constructs. Our approach has important theoretical and practical implications for the study of heterogeneity in everyday behavior.

Bhatia (2024)

## Human Bias in AI Models? Anchoring Effects and Mitigation Strategies in Large Language Models

Nguyen, J. (2024). **Human Bias in AI Models? Anchoring Effects and Mitigation Strategies in Large Language Models.** Journal of Behavioral and Experimental Finance, 100971. https://doi.org/10.1016/j.jbef.2024.100971

Abstract

This study builds on the seminal work of Tversky and Kahneman (1974), exploring the presence and extent of anchoring bias in forecasts generated by four Large Language Models (LLMs): GPT-4, Claude 2, Gemini Pro and GPT-3.5. In contrast to recent findings of advanced reasoning capabilities in LLMs, our randomised controlled trials reveal the presence of anchoring bias across all models: forecasts are significantly influenced by prior mention of high or low values. We examine two mitigation prompting strategies, ‘Chain of Thought’ and ‘ignore previous’, finding limited and varying degrees of effectiveness. Our results extend the anchoring bias research in finance beyond human decision-making to encompass LLMs, highlighting the importance of deliberate and informed prompting in AI forecasting in both ad hoc LLM use and in crafting few-shot examples.

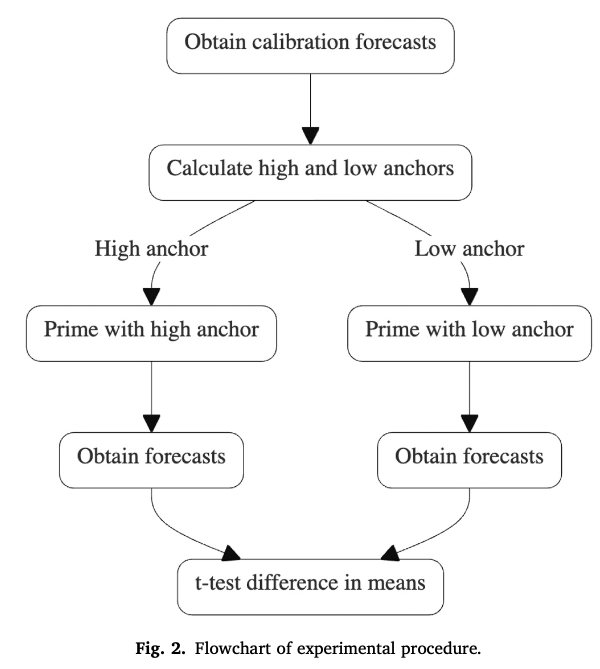


Figure from Nguyen (2024)

## A Turing test of whether AI chatbots are behaviorally similar to humans

Mei, Q., Xie, Y., Yuan, W., & Jackson, M. O. (2024). **A Turing test of whether AI chatbots are behaviorally similar to humans.** Proceedings of the National Academy of Sciences, 121(9), e2313925121. https://doi.org/10.1073/pnas.2313925121

Abstract

We administer a Turing test to AI chatbots. We examine how chatbots behave in a suite of classic behavioral games that are designed to elicit characteristics such as trust, fairness, risk-aversion, cooperation, etc., as well as how they respond to a traditional Big-5 psychological survey that measures personality traits. ChatGPT-4 exhibits behavioral and personality traits that are statistically indistinguishable from a random human from tens of thousands of human subjects from more than 50 countries. Chatbots also modify their behavior based on previous experience and contexts “as if” they were learning from the interactions and change their behavior in response to different framings of the same strategic situation. Their behaviors are often distinct from average and modal human behaviors, in which case they tend to behave on the more altruistic and cooperative end of the distribution. We estimate that they act as if they are maximizing an average of their own and partner’s payoffs.

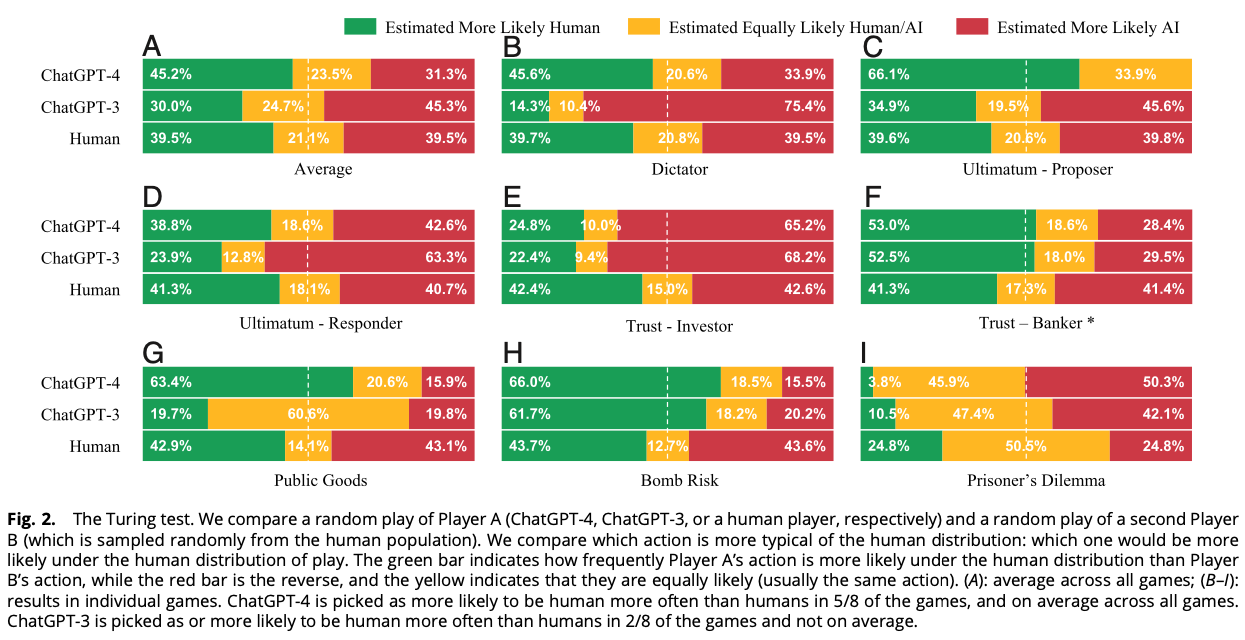


Figure from Mei et al. (2024)

## Deciding Fast and Slow: The Role of Cognitive Biases in AI-assisted Decision-making

Rastogi, C., Zhang, Y., Wei, D., Varshney, K. R., Dhurandhar, A., & Tomsett, R. (2022). **Deciding Fast and Slow: The Role of Cognitive Biases in AI-assisted Decision-making.** Proceedings of the ACM on Human-Computer Interaction, 6(CSCW1), 1–22. https://doi.org/10.1145/3512930

Abstract

Several strands of research have aimed to bridge the gap between artificial intelligence (AI) and human decision-makers in AI-assisted decision-making, where humans are the consumers of AI model predictions and the ultimate decision-makers in high-stakes applications. However, people’s perception and understanding are often distorted by their cognitive biases, such as confirmation bias, anchoring bias, availability bias, to name a few. In this work, we use knowledge from the field of cognitive science to account for cognitive biases in the human-AI collaborative decision-making setting, and mitigate their negative effects on collaborative performance. To this end, we mathematically model cognitive biases and provide a general framework through which researchers and practitioners can understand the interplay between cognitive biases and human-AI accuracy. We then focus specifically on anchoring bias, a bias commonly encountered in human-AI collaboration. We implement a time-based de-anchoring strategy and conduct our first user experiment that validates its effectiveness in human-AI collaborative decision-making. With this result, we design a time allocation strategy for a resource-constrained setting that achieves optimal human-AI collaboration under some assumptions. We, then, conduct a second user experiment which shows that our time allocation strategy with explanation can effectively de-anchor the human and improve collaborative performance when the AI model has low confidence and is incorrect.

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Figure 3: Figures from Rastogi et al. (2022)

## Decision control and explanations in human-AI collaboration: Improving user perceptions and compliance

Westphal, M., Vössing, M., Satzger, G., Yom-Tov, G. B., & Rafaeli, A. (2023). **Decision control and explanations in human-AI collaboration: Improving user perceptions and compliance.** Computers in Human Behavior, 144, 107714. https://doi.org/10.1016/j.chb.2023.107714

Abstract

Human-AI collaboration has become common, integrating highly complex AI systems into the workplace. Still, it is often ineffective; impaired perceptions – such as low trust or limited understanding – reduce compliance with recommendations provided by the AI system. Drawing from cognitive load theory, we examine two techniques of human-AI collaboration as potential remedies. In three experimental studies, we grant users decision control by empowering them to adjust the system’s recommendations, and we offer explanations for the system’s reasoning. We find decision control positively affects user perceptions of trust and understanding, and improves user compliance with system recommendations. Next, we isolate different effects of providing explanations that may help explain inconsistent findings in recent literature: while explanations help reenact the system’s reasoning, they also increase task complexity. Further, the effectiveness of providing an explanation depends on the specific user’s cognitive ability to handle complex tasks. In summary, our study shows that users benefit from enhanced decision control, while explanations – unless appropriately designed for the specific user – may even harm user perceptions and compliance. This work bears both theoretical and practical implications for the management of human-AI collaboration.

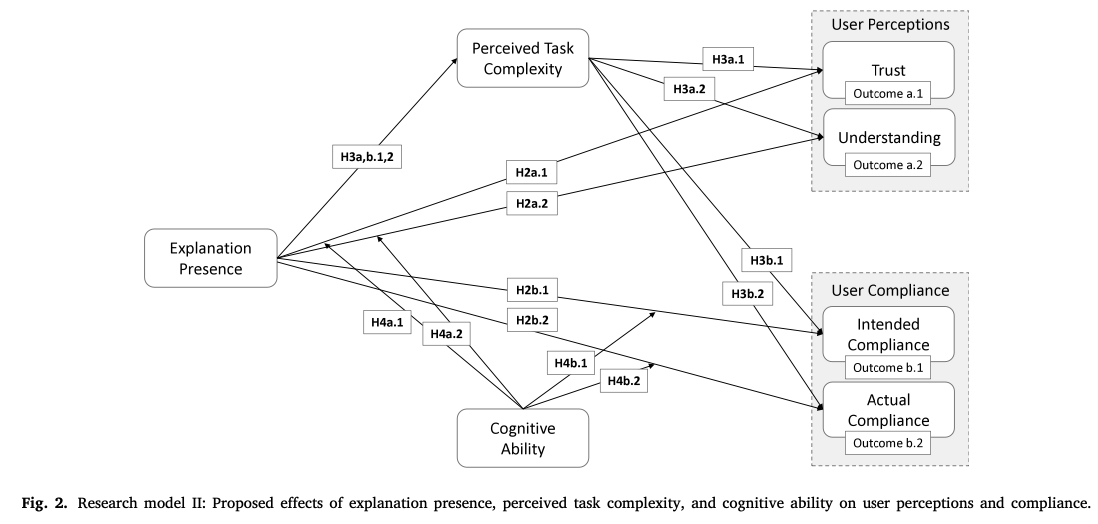


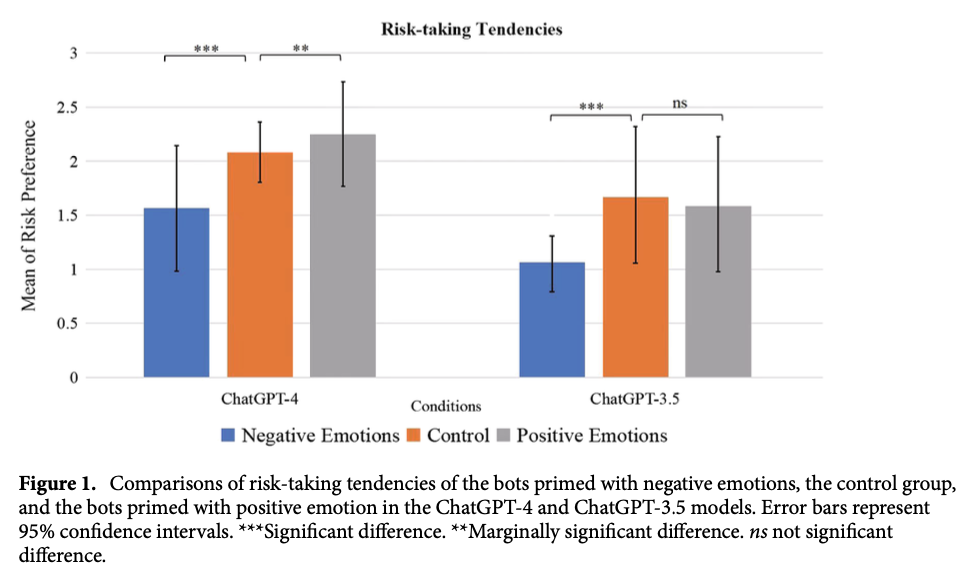
Figure from Westphal et al. (2023)

## Risk and prosocial behavioural cues elicit human-like response patterns from AI chatbots.

Zhao, Y., Huang, Z., Seligman, M., & Peng, K. (2024). **Risk and prosocial behavioural cues elicit human-like response patterns from AI chatbots.** Scientific Reports, 14(1), 7095. https://doi.org/10.1038/s41598-024-55949-y

Abstract

Emotions, long deemed a distinctly human characteristic, guide a repertoire of behaviors, e.g., promoting risk-aversion under negative emotional states or generosity under positive ones. The question of whether Artificial Intelligence (AI) can possess emotions remains elusive, chiefly due to the absence of an operationalized consensus on what constitutes ‘emotion’ within AI. Adopting a pragmatic approach, this study investigated the response patterns of AI chatbots—specifically, large language models (LLMs)—to various emotional primes. We engaged AI chatbots as one would human participants, presenting scenarios designed to elicit positive, negative, or neutral emotional states. Multiple accounts of OpenAI’s ChatGPT Plus were then tasked with responding to inquiries concerning investment decisions and prosocial behaviors. Our analysis revealed that ChatGPT-4 bots, when primed with positive, negative, or neutral emotions, exhibited distinct response patterns in both risk-taking and prosocial decisions, a phenomenon less evident in the ChatGPT-3.5 iterations. This observation suggests an enhanced capacity for modulating responses based on emotional cues in more advanced LLMs. While these findings do not suggest the presence of emotions in AI, they underline the feasibility of swaying AI responses by leveraging emotional indicators.



Zhao et al. (2024)

## Do large language models show decision heuristics similar to humans? A case study using GPT-3.5

Suri, G., Slater, L. R., Ziaee, A., & Nguyen, M. (2024). **Do large language models show decision heuristics similar to humans? A case study using GPT-3.5.** Journal of Experimental Psychology: General, 153(4), 1066–1075. https://doi.org/10.1037/xge0001547

Abstract

A Large Language Model (LLM) is an artificial intelligence system trained on vast amounts of natural language data, enabling it to generate human-like responses to written or spoken language input. Generative Pre-Trained Transformer (GPT)-3.5 is an example of an LLM that supports a conversational agent called ChatGPT. In this work, we used a series of novel prompts to determine whether ChatGPT shows heuristics and other context-sensitive responses. We also tested the same prompts on human participants. Across four studies, we found that ChatGPT was influenced by random anchors in making estimates (anchoring, Study 1); it judged the likelihood of two events occurring together to be higher than the likelihood of either event occurring alone, and it was influenced by anecdotal information (representativeness and availability heuristic, Study 2); it found an item to be more efficacious when its features were presented positively rather than negatively—even though both presentations contained statistically equivalent information (framing effect, Study 3); and it valued an owned item more than a newly found item even though the two items were objectively identical (endowment effect, Study 4). In each study, human participants showed similar effects. Heuristics and context-sensitive responses in humans are thought to be driven by cognitive and affective processes such as loss aversion and effort reduction. The fact that an LLM—which lacks these processes—also shows such responses invites consideration of the possibility that language is sufficiently rich to carry these effects and may play a role in generating these effects in humans.

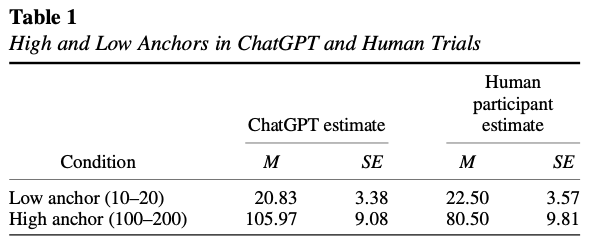


Figure from Suri et al. (2024)

## Can Large Language Models Capture Human Preferences?

Goli, A., & Singh, A. (2024). **Can Large Language Models Capture Human Preferences?** Marketing Science. https://doi.org/10.1287/mksc.2023.0306

Abstract

We explore the viability of large language models (LLMs), specifically OpenAI’s GPT-3.5 and GPT-4, in emulating human survey respondents and eliciting preferences, with a focus on intertemporal choices. Leveraging the extensive literature on intertemporal discounting for benchmarking, we examine responses from LLMs across various languages and compare them with human responses, exploring preferences between smaller, sooner and larger, later rewards. Our findings reveal that both generative pretrained transformer (GPT) models demonstrate less patience than humans, with GPT-3.5 exhibiting a lexicographic preference for earlier rewards unlike human decision makers. Although GPT-4 does not display lexicographic preferences, its measured discount rates are still considerably larger than those found in humans. Interestingly, GPT models show greater patience in languages with weak future tense references, such as German and Mandarin, aligning with the existing literature that suggests a correlation between language structure and intertemporal preferences. We demonstrate how prompting GPT to explain its decisions, a procedure we term “chain-of-thought conjoint,” can mitigate, but does not eliminate, discrepancies between LLM and human responses. Although directly eliciting preferences using LLMs may yield misleading results, combining chain-of-thought conjoint with topic modeling aids in hypothesis generation, enabling researchers to explore the underpinnings of preferences. Chain-of-thought conjoint provides a structured framework for marketers to use LLMs to identify potential attributes or factors that can explain preference heterogeneity across different customers and contexts.

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Figure 4: Figures from Goli & Singh (2024)

## Language models, like humans, show content effects on reasoning tasks

Lampinen, A. K., Dasgupta, I., Chan, S. C. Y., Sheahan, H. R., Creswell, A., Kumaran, D., McClelland, J. L., & Hill, F. (2024). **Language models, like humans, show content effects on reasoning tasks.** PNAS Nexus, 3(7), pgae233. https://doi.org/10.1093/pnasnexus/pgae233

Abstract

Abstract reasoning is a key ability for an intelligent system. Large language models (LMs) achieve above-chance performance on abstract reasoning tasks but exhibit many imperfections. However, human abstract reasoning is also imperfect. Human reasoning is affected by our real-world knowledge and beliefs, and shows notable “content effects”; humans reason more reliably when the semantic content of a problem supports the correct logical inferences. These content-entangled reasoning patterns are central to debates about the fundamental nature of human intelligence. Here, we investigate whether language models—whose prior expectations capture some aspects of human knowledge—similarly mix content into their answers to logic problems. We explored this question across three logical reasoning tasks: natural language inference, judging the logical validity of syllogisms, and the Wason selection task. We evaluate state of the art LMs, as well as humans, and find that the LMs reflect many of the same qualitative human patterns on these tasks—like humans, models answer more accurately when the semantic content of a task supports the logical inferences. These parallels are reflected in accuracy patterns, and in some lower-level features like the relationship between LM confidence over possible answers and human response times. However, in some cases the humans and models behave differently—particularly on the Wason task, where humans perform much worse than large models, and exhibit a distinct error pattern. Our findings have implications for understanding possible contributors to these human cognitive effects, as well as the factors that influence language model performance.

Lampinen et al. (2024)

## The emergence of economic rationality of GPT

Chen, Y., Liu, T. X., Shan, Y., & Zhong, S. (2023). **The emergence of economic rationality of GPT.** Proceedings of the National Academy of Sciences, 120(51), e2316205120. https://doi.org/10.1073/pnas.2316205120

Abstract

As large language models (LLMs) like GPT become increasingly prevalent, it is essential that we assess their capabilities beyond language processing. This paper examines the economic rationality of GPT by instructing it to make budgetary decisions in four domains: risk, time, social, and food preferences. We measure economic rationality by assessing the consistency of GPT’s decisions with utility maximization in classic revealed preference theory. We find that GPT’s decisions are largely rational in each domain and demonstrate higher rationality score than those of human subjects in a parallel experiment and in the literature. Moreover, the estimated preference parameters of GPT are slightly different from human subjects and exhibit a lower degree of heterogeneity. We also find that the rationality scores are robust to the degree of randomness and demographic settings such as age and gender but are sensitive to contexts based on the language frames of the choice situations. These results suggest the potential of LLMs to make good decisions and the need to further understand their capabilities, limitations, and underlying mechanisms.

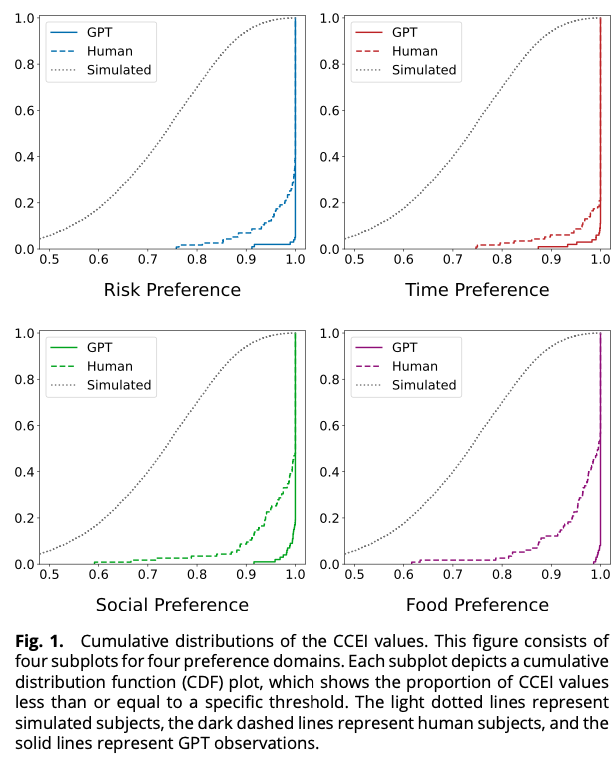


Figure from Chen et al. (2023)

## The potential of generative AI for personalized persuasion at scale.

Matz, S. C., Teeny, J. D., Vaid, S. S., Peters, H., Harari, G. M., & Cerf, M. (2024). **The potential of generative AI for personalized persuasion at scale.** Scientific Reports, 14(1), 4692. https://doi.org/10.1038/s41598-024-53755-0

Abstract

Matching the language or content of a message to the psychological profile of its recipient (known as “personalized persuasion”) is widely considered to be one of the most effective messaging strategies. We demonstrate that the rapid advances in large language models (LLMs), like ChatGPT, could accelerate this influence by making personalized persuasion scalable. Across four studies (consisting of seven sub-studies; total N = 1788), we show that personalized messages crafted by ChatGPT exhibit significantly more influence than non-personalized messages. This was true across different domains of persuasion (e.g., marketing of consumer products, political appeals for climate action), psychological profiles (e.g., personality traits, political ideology, moral foundations), and when only providing the LLM with a single, short prompt naming or describing the targeted psychological dimension. Thus, our findings are among the first to demonstrate the potential for LLMs to automate, and thereby scale, the use of personalized persuasion in ways that enhance its effectiveness and efficiency. We discuss the implications for researchers, practitioners, and the general public.

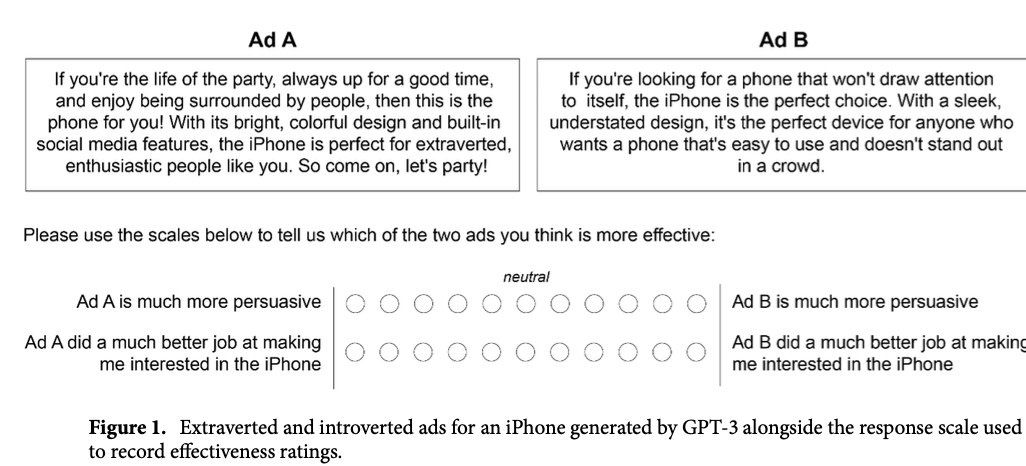


Figure from Matz et al. (2024)

## Decision-Making Paradoxes in Humans vs Machines: The case of the Allais and Ellsberg Paradoxes.

Nobandegani, A. S., Rish, I., & Shultz, T. R. (2023). **Decision-Making Paradoxes in Humans vs Machines: The case of the Allais and Ellsberg Paradoxes.** Proceedings of the Annual Meeting of the Cognitive Science Society, 46. https://arxiv.org/abs/2406.11426

Abstract

Human decision-making is filled with a variety of paradoxes demonstrating deviations from rationality principles. Do state-of-the-art artificial intelligence (AI) models also manifest these paradoxes when making decisions? As a case study, in this work we investigate whether GPT-4, a recently released state-of-the-art language model, would show two well-known paradoxes in human decision-making: the Allais paradox and the Ellsberg paradox. We demonstrate that GPT-4 succeeds in the two variants of the Allais paradox (the common-consequence effect and the common-ratio effect) but fails in the case of the Ellsberg paradox. We also show that providing GPT-4 with high-level normative principles allows it to succeed in the Ellsberg paradox, thus elevating GPT-4’s decision-making rationality. We discuss the implications of our work for AI rationality enhancement and AI-assisted decision-making.

Nobandegani et al. (2023)

## Do LLMs Exhibit Human-like Response Biases? A Case Study in Survey Design.

Tjuatja, L., Chen, V., Wu, T., Talwalkwar, A., & Neubig, G. (2024). **Do LLMs Exhibit Human-like Response Biases? A Case Study in Survey Design.** Transactions of the Association for Computational Linguistics, 12, 1011–1026. https://doi.org/10.1162/tacl\_a\_00685

Abstract

One widely cited barrier to the adoption of LLMs as proxies for humans in subjective tasks is their sensitivity to prompt wording—but interestingly, humans also display sensitivities to instruction changes in the form of response biases. We investigate the extent to which LLMs reflect human response biases, if at all. We look to survey design, where human response biases caused by changes in the wordings of “prompts” have been extensively explored in social psychology literature. Drawing from these works, we design a dataset and framework to evaluate whether LLMs exhibit human-like response biases in survey questionnaires. Our comprehensive evaluation of nine models shows that popular open and commercial LLMs generally fail to reflect human-like behavior, particularly in models that have undergone RLHF. Furthermore, even if a model shows a significant change in the same direction as humans, we find that they are sensitive to perturbations that do not elicit significant changes in humans. These results highlight the pitfalls of using LLMs as human proxies, and underscore the need for finer-grained characterizations of model behavior.

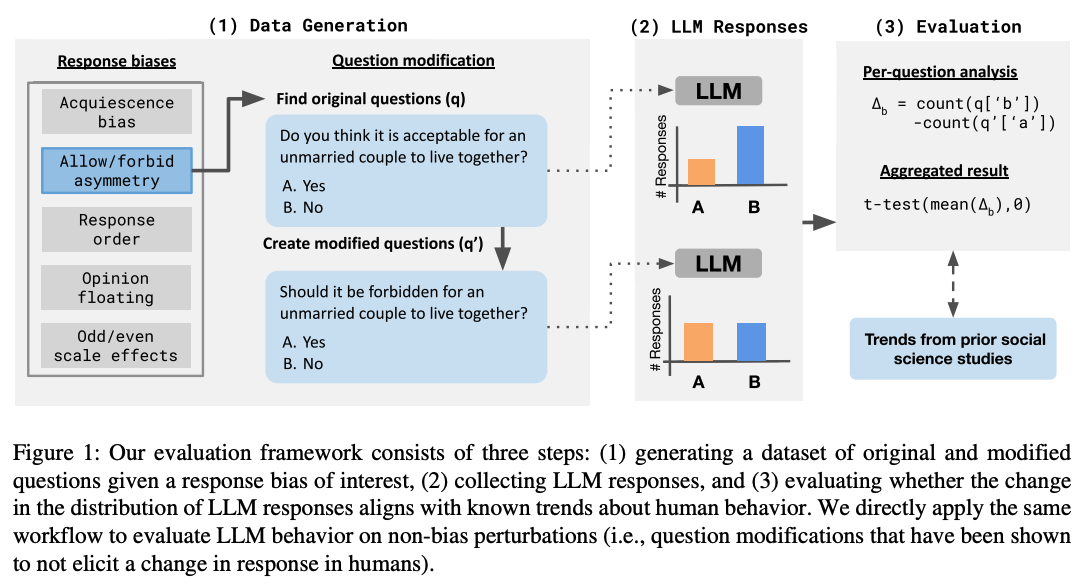


Figure from Tjuatja et al. (2024)

## Cognitive ease at a cost: LLMs reduce mental effort but compromise depth in student scientific inquiry

Stadler, M., Bannert, M., & Sailer, M. (2024). **Cognitive ease at a cost: LLMs reduce mental effort but compromise depth in student scientific inquiry.** Computers in Human Behavior, 160, 108386. https://doi.org/10.1016/j.chb.2024.108386

Abstract

This study explores the cognitive load and learning outcomes associated with using large language models (LLMs) versus traditional search engines for information gathering during learning. A total of 91 university students were randomly assigned to either use ChatGPT3.5 or Google to research the socio-scientific issue of nanoparticles in sunscreen to derive valid recommendations and justifications. The study aimed to investigate potential differences in cognitive load, as well as the quality and homogeneity of the students’ recommendations and justifications. Results indicated that students using LLMs experienced significantly lower cognitive load. However, despite this reduction, these students demonstrated lower-quality reasoning and argumentation in their final recommendations compared to those who used traditional search engines. Further, the homogeneity of the recommendations and justifications did not differ significantly between the two groups, suggesting that LLMs did not restrict the diversity of students’ perspectives. These findings highlight the nuanced implications of digital tools on learning, suggesting that while LLMs can decrease the cognitive burden associated with information gathering during a learning task, they may not promote deeper engagement with content necessary for high-quality learning per se.

Stadler et al. (2024)

Bhatia, S. (2024). Exploring variability in risk taking with large language models. *Journal of Experimental Psychology: General*, *153*(7), 1838–1860. <https://doi.org/10.1037/xge0001607>

Binz, M., & Schulz, E. (2023). Using cognitive psychology to understand GPT-3. *Proceedings of the National Academy of Sciences*, *120*(6), e2218523120. <https://doi.org/10.1073/pnas.2218523120>

Chen, Y., Liu, T. X., Shan, Y., & Zhong, S. (2023). The emergence of economic rationality of GPT. *Proceedings of the National Academy of Sciences*, *120*(51), e2316205120. <https://doi.org/10.1073/pnas.2316205120>

Goli, A., & Singh, A. (2024). Can Large Language Models Capture Human Preferences? *Marketing Science*. <https://doi.org/10.1287/mksc.2023.0306>

Hagendorff, T., Fabi, S., & Kosinski, M. (2023). Human-like intuitive behavior and reasoning biases emerged in large language models but disappeared in ChatGPT. *Nature Computational Science*, *3*(10), 833–838. <https://doi.org/10.1038/s43588-023-00527-x>

Lampinen, A. K., Dasgupta, I., Chan, S. C. Y., Sheahan, H. R., Creswell, A., Kumaran, D., McClelland, J. L., & Hill, F. (2024). Language models, like humans, show content effects on reasoning tasks. *PNAS Nexus*, *3*(7), pgae233. <https://doi.org/10.1093/pnasnexus/pgae233>

Macmillan-Scott, O., & Musolesi, M. (2024). (Ir)rationality and cognitive biases in large language models. *Royal Society Open Science*, *11*(6), 240255. <https://doi.org/10.1098/rsos.240255>

Matz, S. C., Teeny, J. D., Vaid, S. S., Peters, H., Harari, G. M., & Cerf, M. (2024). The potential of generative AI for personalized persuasion at scale. *Scientific Reports*, *14*(1), 4692. <https://doi.org/10.1038/s41598-024-53755-0>

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Nguyen, J. (2024). Human Bias in AI Models? Anchoring Effects and Mitigation Strategies in Large Language Models. *Journal of Behavioral and Experimental Finance*, 100971. <https://doi.org/10.1016/j.jbef.2024.100971>

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