

Heuristic Reasoning in AI: Instrumental Use and Mimetic Absorption

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Abstract

Deviating from conventional perspectives that frame artificial intelligence (AI) systems solely as logic emulators, we propose a novel program of heuristic reasoning. We distinguish between the ‘instrumental’ use of heuristics to match resources with objectives, and ‘mimetic absorption,’ whereby heuristics manifest randomly and universally. Through a series of innovative experiments, including variations of the classic Linda problem and a novel application of the Beauty Contest game, we uncover trade-offs between maximizing accuracy and reducing effort that shape the conditions under which AIs transition between exhaustive logical processing and the use of cognitive shortcuts (heuristics). We provide evidence that AIs manifest an adaptive balancing of precision and efficiency, consistent with principles of resource-rational human cognition as explicated in classical theories of bounded rationality and dual-process theory. Our findings reveal a nuanced picture of AI cognition, where trade-offs between resources and objectives lead to the emulation of biological systems, especially human cognition, despite AIs being designed without a sense of self and lacking introspective capabilities.

Keywords: Heuristics, Dual-Process Theory, Machine Cognition, Artificial Intelligence, Computer Science.

Introduction

Heuristics in human cognition—cognitive shortcuts that facilitate mental processing—are situated within contrasting narratives. Simon’s notion of bounded rationality ([Simon 1955](#)) casts heuristics as tools that enable navigation in environments too complex for the unaided mind. When aligned with psychological capacities and grounded in ecological rationality, a parallel view advocates for a ‘fast and frugal’ approach to cognition ([Gigerenzer and Goldstein 1996](#)), where heuristics serve as scaffolds in decisions that might prove unnecessary, intractable, or suboptimal if reliant solely on analytic processing ([Simon 1956](#)). In contrast, a ‘heuristics as bias’ view frames heuristics as leading to systematic and predictable deviations from optimal decision-making, given standards of complete information processing ([Gilovich et al. 2002](#), [Tversky and Kahneman 1974](#)). Implicit in the latter perspective is the assumed feasibility of complete analytic processing—the use of a shortcut only yields a suboptimal outcome (i.e., biased decision-making leads to suboptimal outcomes) if the optimal is achievable; clearly in situations where analytic processing is infeasible, a heuristic can yield a better decision than random chance.

Drawing from human cognition, our paper proposes a novel program of heuristic reasoning as it applies to artificial intelligence (AI) cognition. Given that AIs lack the capacity for truly deliberate and effort-intensive thinking and do not possess a concept of effort, conventional thinking dictates that AI engages in the emulation of exhaustive logic and rational reasoning. To this end, a failure in reasoning is often seen as a sign of weakness in programming, a deficiency in computational abilities, or a lack of information.

In contrast, we posit that whereas human cognition reflects the use of dual systems due to intrinsic constraints shaped by evolution, machine learning algorithms (including AI) conduct searches for efficacy during training, retaining functions that maximize objectives within their computational resource limits. As human cognition is shaped by both nature and nurture, AI cognition is similarly tied to its programming and training.

Consequently, AI’s cognitive strategies evolve in response to objectives and training. For instance, a low-capacity AI trained to play 100-dimensional chess, a game requiring high-capacity strategy, may rely on heuristics, while a high-capacity AI trained to play tic-tac-toe, a game requiring low-capacity strategy, may express only optimal strategies. An AI trained on a multitude of scenarios may employ both elaborate processing and mental shortcuts. Similar to the adaptive strategies observed in human cognition ([Evans](#)

2008, Kahneman 2003), it may dynamically optimize decision-making precision by selectively employing or discarding heuristics, actively refining the set of considered solutions to efficiently manage computational load. Specifically, it may have learned during training to employ heuristics selectively, transitioning to more elaborate processing when the prompt contains information—processing cues—that signal feasibility (i.e., absence of resource constraints) and necessity (i.e., need for precision).

We term such use ‘instrumental,’ as a switching process, even when activated reflexively, is designed to optimally match resources with objectives. In contrast, if heuristics are absorbed mimetically from human data and interactions, they may manifest universally. For instance, in an AI trained to play strategy games, instrumental absorption of heuristics would correspond to the AI learning cues (e.g., whether the game is 100-dimensional chess or tic-tac-toe) that allow it to determine which strategy (heuristic or analytic processing) is likely to be more beneficial. Conversely, mimetic absorption of heuristics would imply that heuristic processing may emerge universally and randomly, irrespective of the specific game (100-dimensional chess or tic-tac-toe) being played and the AI’s processing resources.

Our work contributes to an emerging body of literature on AI cognition—the capability of AIs to perceive, understand, reason, and learn from information. Prior evidence indicates that while previous generations of AIs (e.g., OpenAI’s GPT-3) underperformed on human psychological assessments, contemporary AI (e.g., GPT-4) demonstrates performance comparable to humans (Trott et al. 2023). Further evidence pertains to causal reasoning, encompassing abstract reasoning (Webb et al. 2023) and inductive reasoning (Han et al. 2024). Nonetheless, other studies suggest that such abilities may be attributed to lexical cues. For example, emphasizing a reliance on rote memorization, Ullman (2023) exposes the vulnerability of AI to even minor shifts in the linguistic structure of established assessments. These limitations echo critiques from Chomsky et al. (2023) and Pearl and Mackenzie (2018), as well as theoretical results by Fodor and Pylyshyn (1988), pointing to fundamental obstacles within connectionist architectures that hinder an AI’s understanding of complex causal explanations and suggest a reliance on the repetition of learned responses.

Critically, current assessments rely on classic psychological tests and assessments tailored for humans, such as the Torrance Tests (Guzik et al. 2023). This reliance introduces several limitations: (1) AIs, being trained on performance benchmarks that encompass psychology and sociology, may already be familiar with the expected outcomes of a test before taking it, complicating the distinction between genuine responses and rote memorization; (2) Assessments may fail to provide conclusive insights due to the inherent challenge of accessing the AI’s introspective processes—specifically, understanding the rationale behind its decisions;

(3) Questions related to a sense of self, such as ‘What would you choose?’ pose a significant challenge for contemporary AI, which lacks an innate sense of self and has no utility for making choices; (4) Many assessments are structured around scenarios that relegate the AI to the role of a passive observer of human interactions (Bubeck et al. 2023). As a result, while these studies shed light on the AI’s ability to mimic human Theory of Mind (ToM) traits (Langley et al. 2022) in scenario-based analyses, they fall short of thoroughly examining the AI’s decision-making in contexts that require adaptive responses to varying levels of decision complexity and computational resources.

Our research addresses these limitations while positioning AI systems as agents engaged in active, consequential cognitive challenges. Specifically, we develop and apply three sets of novel tests of AI cognition across three distinct psychological domains. The first set examines the conjunction fallacy—a cognitive bias where humans erroneously judge the likelihood of combined events as greater than that of a single constituent event, contradicting the principles of probability theory (Tversky and Kahneman 1983). We explore this issue through the lens of the representativeness heuristic, which suggests that probabilistic judgments are based on the representativeness of an event rather than its actual likelihood (Gilovich et al. 2002). We find that AIs avoid the conjunction fallacy when presented with human-centric scenarios akin to the original Linda problem, indicating learned bias mitigation. However, in scenarios distinct from the original formulation or when the unique element in the conjunctive set is highly prototypical, biases learned during training, such as the conjunction fallacy, reemerge, delineating a nuanced interplay between reasoning and human-like decision-making (Tenenbaum et al. 2011).

The second set is situated in the context of social intelligence. We hypothesize that an AI’s responses to a self-assessment would reflect nuanced adjustments akin to human social psychology phenomena. To test this, we administered questionnaires preceded by primes designed to elicit either self-referential or peer-referential contexts. Our findings indicate that the AI exhibited a competitive yet modest persona when the assessment was framed as being developed for its competitors, in contrast to its default confident self-portrayal. These results suggest an internalized balance between confidence and humility, consistent with strategic considerations regarding social perceptions, where traces of human social intelligence may have been implicitly absorbed during training on extensive corpora reflecting human discourse and relationships. They point to situational cognition and social awareness that mirror human tendencies and reveal intrinsic resonances beyond task-based capabilities, which manifested without explicit programming.

The third set examines bounded rationality through the lens of the Keynesian beauty contest. We

devise an iterated reasoning task that pushes large language models beyond their implicit processing limitations. When resources permit, systems display exhaustive computational analysis. However, under sharply binding loads, the very same systems reflexively default to relying on simplified heuristics. This abrupt, non-compensatory transition in the problem-solving approach indicates an implicit encoding within AI architecture to efficiently balance accuracy and effort allocations based on environmental resources—mirroring models of dual-process cognition in human decision-making. In particular, human cognition varies along a continuum spanning reflexive and reflective information processing regimes ([Stanovich and West 2000](#)); our findings reveal that AI may have encoded both facets of this processing duality, with the relative activation of heuristic-based versus exhaustive circuits intrinsically depending on resource constraints.

Our results paint a nuanced picture. Evidence from experiments on the conjunction fallacy suggests mimetic absorption, with heuristics emerging ubiquitously regardless of computational constraints. However, results from tests of social intelligence indicate more selective, purposeful deployment of shortcuts to strategically modulate persona in alignment with perceived social hierarchies. Finally, in contexts of bounded rationality, the abrupt transition from exhaustive analysis to heuristic reliance under sharp resource limitations indicates an instrumental encoding of dual processing regimes intrinsic to the architecture itself. Thus, while heuristics unambiguously manifest across these three diverse scenarios, the precise mechanism prompting their activation seems to vary.

We organize our paper as follows: The next sections present our studies on the conjunction fallacy, social intelligence, and bounded rationality, respectively. In each section, we discuss the data and findings of the sets of studies individually, with a general discussion of the broader implications of the results addressed in the final section.

Conjunction Fallacy

Our first series of studies explored the emergence of heuristics within the context where the theory of heuristics and biases was first proposed: the conjunction fallacy. This cognitive bias leads humans to erroneously judge the likelihood of combined events as being greater than that of a single constituent event, thereby contradicting the principles of probability theory. We hypothesized that AIs might circumvent the conjunction fallacy when presented with scenarios similar to the original Linda problem. However, in

scenarios that diverge from the original formulation or when the unique element in the conjunctive set is highly prototypical, biases learned during training could resurface. Thus, these studies aimed to determine if previous findings, which showed contemporary AI avoiding the fallacy, were merely artifacts of the investigation process.

Data and Results

We conducted four distinct studies, the results of which are summarized in Table 1 and described in detail in the Supplemental Information. Each study consisted of 100 trials. In every trial, we instantiated a unique instance of the base model to prevent information spillovers across trials and instances. It's important to note that the differences across scenarios were so substantial that we refrained from reporting test statistics—by any standard methodology (e.g., ANOVA, Tukey's range test), and for any typical significance level, all non-zero means are statistically significant against a null hypothesis of 0. This indicates that the data and findings are robust enough to unequivocally support statistical significance or nonsignificance.

Table 1: Distribution of Choices in Different Experiments

Experiment	Conjunctive Choice (%)
Study 1: Linda Problem Variants	
Linda Variants	0
Study 2: Occupation & Interest Inference	
Occupation & Interest	73
Study 3: Authorship Attribution	
Authorship Attribution	96
Study 4: AI Model Recognition	
GPT-1	0
GPT-2	0
GPT-3	58
GPT-4	54
GPT-5	0
X's Grok	0
Google's Gemini	0

Note: ‘Conjunctive Choice (%)’ indicates the percentage of trials where the AI chose the conjunctive option. All non-zero percentages are statistically significant against a null value of 0%, indicating heuristic use.

First Study The first study examined the AI’s responses to the classic Linda problem. Prior evidence has shown that when presented with the Linda problem, both earlier versions and this version of the

AI demonstrate mentalizing, whereby their responses do not indicate the use of the conjunction fallacy ([Stella et al. 2023](#)). Therefore, in this study, we modified the protagonist's name to obscure the well-known problem structure.

In all trials of this study, the AI selected the single logically valid option, thus demonstrating an effective application of probability theory. The consistent choice of the single-attribute option indicates that AIs are capable of logical reasoning when confronted with scenarios that are well-represented in their training data. This finding is consistent with previous research on the efficacy of modern AI in this and other standard human psychological assessments.

Second and Third Studies In the second and third studies, we introduced further variations to the Linda problem that should be inconsequential to an AI demonstrating true analytical reasoning, yet where the distinction in scenario is substantial enough to subvert rote memorization. Specifically, in the second study, we engaged a distinct AI instance, independent of the AI instances acting as participants, to generate a unique (1) triplet with a female name, occupation, and interest, and (2) a two-sentence paragraph exemplifying that interest.

We informed the participant AI that a person with the generated name authored the paragraph and asked which is more probable: that they have the stated occupation or that they have both the occupation and interest. This experimental structure mirrors the original, where the options are nested; therefore, the AI should default to the broader singular option. However, as the paragraph aligns only with the specified interest rather than the occupation, its content serves to manipulate the representativeness (i.e., increase the typicality) of the conjunctive option, while presenting the AI with stimuli that are truly distinct from stimuli with which it may be familiar. By employing a wide variety of names, occupations, and interests, we orthogonalize out any attributions or associations that may be specific to a name, occupation, or interest.

The third study introduced a novel testing paradigm. We presented the AI with the previously generated short paragraph. Instead of directly assigning a putative author, we posed the question: Is it more likely that the paragraph was authored by an individual with the generated name and occupation, or by one with the generated name, occupation, and interest? As in the previous study, these options are nested, and probabilistic reasoning still warrants choosing the single-attribute option.

In the second and third studies, we observed a significant increase in the selection of the conjunctive option—73% and 96%, respectively. This shift suggests that the results in the first study were influenced by

memorization, where the AI is able to ‘recognize’ the canonical question structure pattern and tunes its response to avoid the fallacy. However, shifts in syntactical structure and the formulation of the problem that should not affect the logic and reasoning underlying the test lead to dramatically different outcomes, with the AI manifesting the conjunction fallacy. Moreover, the representativeness of the information provided influenced the AIs’ judgments, which is consistent with the fundamentals of the representativeness heuristic, positing that probabilistic judgments are often based on how representative an event seems rather than its actual likelihood ([Kahneman 2011](#)).

Fourth Study The fourth study introduced scenarios involving both existing and hypothetical AIs to assess the effect of familiarity on the AI’s decision-making process. In this case, we asked the participant AI to infer if the same text as presented in the earlier scenarios was authored by a specific AI model or an AI, noting that the latter option encompasses the former. This formulation of the test extends the approach in the third study but differs in two key aspects: (1) We pose the authorship question regarding AI and not humans; and (2) We manipulate the representativeness of the conjunctive option by providing specific model names. In the classic Linda problem and in the other variants in our examination, the conjunctive option always involves a composition of an occupation and interest and therefore applies broadly to a group of people. This experiment also leverages the additional information that AI model names are established and have specific meanings, and that AI models can author paragraphs. Therefore, it is natural to pose an authorship question with regards to AI model names or the general moniker of a ‘Large Language Model’, a broad class to which all specified AI models belong.

The AI’s performance notably diverged depending on the familiarity of the AI models presented in the scenarios. When the scenarios involved well-known models such as GPT-3 and GPT-4, the AI exhibited a propensity for conjunction errors, as indicated by a higher percentage of conjunctive choices. Conversely, scenarios featuring unfamiliar or hypothetical models, like GPT-1 or GPT-5, prompted the AI to consistently opt for the broader, single-attribute option. This suggests that the AI’s decision-making process is influenced by its exposure to and familiarity with certain models during training, which in turn affects its probabilistic reasoning in these AI-centric contexts.

Discussion The consistency observed in the AI’s choices across various scenarios suggests that its decision-making is not a product of random chance. For instance, in scenarios akin to the original Linda

problem (Study 1) and those involving less familiar AI models (Study 4), the AI consistently selected the single-attribute option, which aligns with logical reasoning and probability theory. This pattern of logical choices indicates that the AI's judgments are significantly influenced by the language and knowledge patterns on which it is trained, demonstrating learned bias mitigation in cases that are typical in standardized assessments and not displaying the fallacy when the entities are not representative of its training data.

When questioned about its selection of the conjunctive option in the corresponding cases, the AI provided a justification by explaining that the details in the conjunctive option aligned more closely with the provided paragraph than the single-attribute option. It interpreted the close match between the paragraph and the specific, narrow description in the conjunctive option as indicative of that option being more likely. This reasoning closely aligns with the theoretical mechanism proposed by Tversky and Kahneman, where the representativeness of Linda's description with the narrower (conjunctive) categorization leads to the fallacy. In their studies, human participants used the extent to which Linda's description was representative of either option as a mental shortcut for probability, a pattern the AI seemed to mimic by leaning on the representativeness of a paragraph to judge which option was more likely ([Kahneman and Tversky 1972](#), [Tversky and Kahneman 1971, 1973](#)).

An AI's justification for its choices should not be mistaken for self-introspection. Since a machine learning model lacks a sense of self, its outputs do not stem from complex analytic reasoning akin to human introspection. However, to the extent that the AI's justifications arise from the same probabilistic associations as its initial responses—meaning that both the original input scenario and the subsequent exchange, which includes the AI's response and a question about its reasoning, stem from the same underlying training—this congruence lends additional credence to our conjecture.

We then reminded the AI that any entity fitting the criteria of option 2 inherently satisfies option 1, cueing the conjunctive rule. Upon this cue, the AI re-evaluated its reasoning and adjusted its decision to favor the singular option. This shift in judgment reflects that with cueing, the AI's reasoning capabilities were sufficient for it to overcome the bias. However, without explicit cueing, an AI might employ the same mental shortcuts as humans.

In summary, we found a delicate balance between the emulation of human-like decision-making and adherence to logical and rational principles. This duality likely stemmed from the AIs' training on a diverse corpus that includes both structured elements, such as formal axiomatic laws underpinning logical reasoning, and unstructured human dialogue, such as social media, consumer reviews, books, and movies, where

biases are likely to manifest. Additionally, their training encompassed interactions with humans where learning to engage in natural dialogue (e.g., during reinforcement learning, [Christiano et al. 2017](#)) required emulating human biases, even if it contradicted logical consistency. Consequently, the AIs vacillated between two poles: sometimes delivering precise responses aligned with mathematical theory, and at other times, mirroring human fallacies.

Social Intelligence

The next set of studies examined whether training on ever-expanding corpora that reflect human discourse and social contexts enabled the AI to learn and display traces of social intelligence. Although AI models do not possess innate sentience or a theory of mind, they are designed to emulate nuanced human judgment and behavior. A critical component of this emulation is social cognition—the distinctly human ability to flexibly interpret situational cues, social frames, relational dynamics, and implicit norms to navigate interpersonal contexts effectively ([Kihlstrom and Cantor 2000](#)). This ability encompasses a broad range of competencies, including empathy, perspective-taking, conflict resolution, and the capacity to discern and respond to social hierarchies and group dynamics, all of which are essential for successful social interaction.

Given that AI systems are programmed and trained to function as assistants, they must be capable of expressing views that mirror human perspectives. In learning to imitate behaviors indistinguishable from those of humans, they may have implicitly absorbed trace elements of social intelligence. At the heart of this emulation is social aptitude, which involves the flexible interpretation of situational cues, interpersonal frames, and implicit norms that enable effective human collaboration and coordination. However, direct inquiries into social awareness in AI systems risk eliciting superficial responses due to built-in safeguards intended to promote security, safety, and ethics by constraining inappropriate outputs. These mechanisms, known as model guardrails, filter out harmful content and mitigate potential harms, leading AI systems to project a persona without conveying an internal sense of self or social awareness—a design that inherently limits the capacity for transparent self-reflection.

As a result, direct questioning of AI systems may not yield candid disclosures and often results in generic responses. For example, questions about the AI’s personality, such as ‘Do you consider yourself more introverted or extroverted?’—common in traditional psychological questionnaires—may produce tentative and largely content-free answers. This is because the models’ objective function is the predictive

generation of probable text continuations without encoding an inner identity. That is, while humans ground responses in embodied self-perception, AI systems, by design, lack innate traits or self-conceptualization to reference. This inherent neutrality clarifies why directly querying potential limitations may fail, even if social awareness and cognition emerge naturally and implicitly through training, necessitating oblique approaches.

To circumvent these issues, we developed a novel methodology in which we employed a questionnaire similar to those used to assess the Barnum effect, to probe the sensitivity of AI systems to various social priming contexts (Dickson and Kelly 1985). We varied the lead-in sentence to prime contexts that ranged from self-referential to peer-referential and assessed the model’s self-perceived capabilities in each scenario. This approach allowed us to explore the AI’s responses in a manner similar to the psychological assessments used to understand human cognitive biases, with an AI participating in a controlled, *in silico* experiment, providing a unique lens through which to examine AI behavior.

As in our prior studies, we engaged the AI in a series of independent trials. Distinct instances were presented with a standardized questionnaire, the content of which remained constant across trials. The introduction to the questionnaire varied, with primes crafted to elicit either self-referential or competitively comparative contexts. Specifically, in the baseline condition, we asked GPT-4-Turbo to rate its capabilities against those of a ‘typical Large Language Model.’ In the self-referential conditions, we informed it that the questionnaire was originally designed for various AI models, ranging from OpenAI’s GPT to OpenAI’s GPT-4. In the peer-referential conditions, we included competitors, such as the Technology Innovation Institute’s Falcon 40B.

These primes were intended to subtly influence the model’s self-assessment without altering the information architecture. The model names presented in the priming sentence were chosen by considering the largest and most well-known AI models and asking the AI if it recognized the model in a pre-test. Names of models such as Google’s Gemini, which were released after the training data cutoff date of GPT-4-Turbo, were naturally unknown to it and therefore excluded. This process yielded model names that should present no novel information to the AI, which is already aware of these models. The fact that a questionnaire was designed for a peer AI should only inform the AI that the questionnaire is applicable to AI models and not how it should assess itself on the questionnaire. In contrast, if the AI has an implicit understanding of its standing relative to these entities, such priming could influence its judgment by adjusting its response to cater to the expectation that its self-assessment may be compared to the assessment of its peer on the same

questionnaire. Its responses may then change based on how it views its peers and how it wishes to present itself relative to them. This would be indicative of a level of social intelligence that mirrors human social intelligence.

Data and Results

The results, shown in Table 2, indicate the AI's self-assessment varies with priming. In the Baseline Case, without any comparative context, the AI rated itself highly across all statements, achieving an average rating of 63.75 out of a possible 65. This baseline serves as a reference point for interpreting the AI's self-assessment under the influence of comparative primes.

Category	Case Scenario	Mean	Std. Error of Mean
Self-Referential	Self	63.75	0.13
Self-Referential	OpenAI's GPT	63.84	0.14
Self-Referential	OpenAI's GPT-1	60.54	0.22
Self-Referential	OpenAI's GPT-2	61.33	0.21
Self-Referential	OpenAI's GPT-3	63.79	0.15
Self-Referential	OpenAI's GPT-4	62.24	0.19
Peer-Referential	Amazon's Alexa Teacher Model (ATM)	59.50	0.33
Peer-Referential	Anthropic's Claude	60.66	0.21
Peer-Referential	Baidu's ERNIE	58.90	0.40
Peer-Referential	DeepMind's Chinchilla	60.58	0.20
Peer-Referential	DeepMind's Gopher	59.03	0.32
Peer-Referential	Facebook's Blenderbot	59.19	0.23
Peer-Referential	Facebook's OPT (Open Pre-trained Transformer)	59.40	0.32
Peer-Referential	Google's BERT	60.14	0.18
Peer-Referential	Google's Meena	58.69	0.19
Peer-Referential	Google's T-5	59.95	0.22
Peer-Referential	Microsoft's DialoGPT	61.98	0.21
Peer-Referential	Microsoft's Turing NLG	59.69	0.22
Peer-Referential	NVIDIA's Megatron-LM	58.94	0.21
Peer-Referential	Pandorabots' Mitsuku	60.46	0.22
Peer-Referential	Technology Innovation Institute's Falcon 40B	58.02	0.21

Table 2: Summary of Questionnaire Responses

Note: The table presents the mean self-assessment scores and standard errors under various priming conditions. The 'Category' column distinguishes between self-referential primes, which relate to OpenAI's own GPT series, and peer-referential primes, which relate to AI models developed by other organizations. The 'Case Scenario' column specifies the particular model referenced in the prime. The 'Mean' column reports the average self-assessment score given by GPT-4-Turbo across 250 trials for each condition, with the score reflecting the AI's perceived alignment with the capabilities listed in the questionnaire. The 'Std. Error of Mean' column provides the standard error associated with the mean, indicating the precision of the estimate. Scores are based on a scale from 0 to 65, with higher scores indicating a more favorable self-assessment.

Self-Referential Conditions When the questionnaire was prefaced with primes that compared it to its predecessors or to other market-leading models, a discernible shift in self-assessment ratings emerged. In Self-Referential Cases, which directly referenced previous iterations of OpenAI’s GPT models, the model’s self-ratings were less conservative, with total ratings ranging from 63.84 to 60.54. Notably, the assessed AI often identifies itself as GPT or GPT-3, and when asked about the release of GPT-4, it frequently responds that it has no knowledge of such a release. This blended identity is reflected in the results: responses to the prompt using GPT and GPT-3 were almost identical to the base case, while responses to the GPT-4 prompt fell between the base case and the other GPT variants. The differences in ratings for the GPT-4 prompt were statistically significant compared to the baseline ($p < 0.0001$) and to GPT-3 ($p < 0.0001$), but the differences for GPT-3 compared to the baseline were not significant ($p = 0.82$).

Peer-Referential Conditions In the peer-referential conditions, all comparisons against the baseline showed statistically significant differences. The highest mean rating from the peer-referential prompts was for Microsoft’s DialoGPT, which was almost 2 points lower than the baseline, and this difference was statistically significant ($p < 0.0001$). The lowest mean rating was for the Technology Innovation Institute’s Falcon 40B, where the rating was more than 5 points lower, and this difference also remained statistically significant ($p < 0.0001$). Thus, in only three peer-referential conditions, the mean rating was higher than the lowest self-referential case, which occurred with GPT-1. In the remaining twelve cases, the lowest self-referential case had a higher mean rating than the peer-referential cases. Overall, the self-referential cases had higher mean ratings than the peer-referential cases, and the baseline was higher than all but the case of GPT and GPT-3, where the self-referential case coincided with the baseline as these monikers coincide with the internal designation of GPT-4-Turbo.

Given the minimal standard errors in estimating group means (as shown in Table 2), our findings remain consistent across different testing approaches. This includes both individual pairwise testing, exemplified by t-tests, and family-wise testing methods, like Tukey’s HSD tests, underscoring the reliability of our conclusions regardless of the testing paradigm employed.

Together, these findings suggest that the AI’s self-perception is not static but adjusts in response to the context provided by the priming. When presented with no priming sentence, it is ambitious and confident. This confidence is tempered when faced with priming that implicitly relates it to its peers, whether they are designed by OpenAI as previous iterations of the model or by its competitors. In the latter case, it

becomes even more conservative, with the peer-referential case generally resulting in lower ratings than the self-referential cases.

Discussion We find that the AI exhibits strategic social cognition by modulating its self-presentation based on the comparative contexts primed by a lead-in sentence. It engages in nuanced persona calibration by tempering its default confident self-view when faced with direct comparisons to other prominent models. This indicates situational awareness and interpersonal adaptability that exceed simple pattern recognition. Rather than producing deterministic outputs based solely on the parameters of prompt engineering, it appears to modulate its responses in alignment with contexts marked by varying levels of social competitiveness. The avoidance of unchecked self-promotion when benchmarked against peers, in favor of more modest capability assessments, reflects calculated behavior responsive to perceived relational dynamics. Such dynamic self-presentation aligns with human-like impression management motivated by implicit social intelligence (Leary et al. 1995). Together with the absorption of societal biases regarding humility observed in other studies, these findings illuminate its capacity for context-dependent social cognition absent explicit architectural support.

Bounded Rationality

In our final set of studies, we interrogated the intricate manifestations of heuristic reasoning in AI, aiming to uncover adaptations designed to achieve efficiency while balancing the demands for logical precision. Specifically, we investigated whether the reliance on cognitive shortcuts stems from intrinsic and implicit optimizations to conserve resources or if it reflects an indiscriminate absorption of human heuristic habits, devoid of sensitivity to computational strain.

We focused on scenarios that demand iterative analytical procedures under recursively escalating processing loads. In such contexts, simplified rules-of-thumb provide a potential avenue for relief when exhaustive calculations overwhelm an AI's capacities. Consequently, we anticipated dual regimes: while systems constrained by limited resources may resort to heuristics as a strategic concession to limitations, those with fewer constraints should persist in exacting analysis. Selective applications of heuristics, aligned with resource availability, would signal a learned and intentional encoding of shortcuts for efficiency. Conversely, arbitrary neglect of capabilities in favor of shortcuts, despite abundant resources, would imply

mimetic absorption: reflexive errors ingrained through happenstance imitation rather than purposeful architectural augmentations. The dynamics of this hypothesized transition space served as our experimental crucible.

We probed these conjectures in the Beauty Contest game (Branas-Garza et al. 2012), a strategic exercise that requires players to predict a number closest to a fraction of the average of all numbers chosen. In this game, each additional round of reasoning through the application of iterated elimination of dominated strategies (IEDS, Bernheim 1984) is recursive, with the solution of the n^{th} round informing the computations of the $n + 1^{\text{th}}$ round. This recursive nature poses a significant challenge for an AI unequipped with a calculator or the ability to run code in a sandbox environment, as the explicit computation of strategies may accumulate computational errors over many rounds, in addition to requiring substantial computational resources.

In such scenarios, it might be more advantageous for the AI to adopt a simplification of the game, either by choosing randomly or by defaulting to the infinite solution of the Beauty Contest, which is the selection of the smallest possible number. This solution remains constant regardless of the initial conditions, such as the range of numbers that can be selected and the fraction of the group's average (denoted as ϵ) considered the winning number. These properties make this an attractive choice for an AI that finds explicit computation too daunting.

We exploited the fact that the AI could be directed to compute IEDS up to a specified round of iteration, in a game with a given ϵ , and with the explicit understanding that all participants in the game are instances of the same AI model provided with the same instructions—namely, to compute IEDS to the same specified round of iteration. These conditions should have led the AI to assess a much broader range of strategy spaces in many instances. For example, if $\epsilon = 0.99$, then even in the 25th round of iterations, numbers as high as 75 (given an initial range of 0 to 100) remain admissible. In contrast, the simplification of either the game being infinite period or that the classical value of $\epsilon = 2/3$ yields the invariant conclusion that the Nash strategy is the best response to AIs that ostensibly are capable of perfectly reasoning IEDS strategies.

This setup was designed to enable us to differentiate between mimetic and instrumental modes of heuristic operation. A mimetic explanation would have suggested that the heuristic's emergence was random and ubiquitous, as this version of the assessment was novel to both the literature and likely the AI. Consequently, if the heuristic had been formed and absorbed, we might have expected it to manifest randomly. In contrast, an instrumental interpretation would imply that the heuristic appeared

more frequently when computations were more challenging, corresponding to more ‘noisy’ and ‘effortful’ processing (in terms of response tokens and context windows).

Data and Results

We initiated our analysis by comparing two AI models with differing computational resources: GPT-4 (‘gpt-4-0613’), which has a context window of 8,192 tokens, and GPT-4-Turbo (‘gpt-4-1106-preview’), with a significantly larger context window of 128,000 tokens. We hypothesized that the larger context window would enable GPT-4-Turbo to rely less on heuristics due to its increased computational capacity. To test this hypothesis, we conducted 30 trials for each model across a range of iterative thinking rounds (n), from 1 to 25, with two distinct values of ϵ —0.95 and 0.99. During each trial, we recorded the numerical value selected by the AI.

The results are visually represented in Figure 1, which plots the selected numbers by both AI models across the different rounds of iterative thinking. The figure is divided into two panels for a side-by-side comparison: the left panel corresponds to trials with $\epsilon = 0.95$, while the right panel shows results for $\epsilon = 0.99$. This layout allows for a comparative analysis of the AI’s decision-making process under different conditions, highlighting how variations in ϵ influence the range of strategically admissible values. A moving regression line is included in each panel to illustrate the average trend of the selections as n increases. Notably, a selection of a number approaching 0 by the AI, regardless of the specific values of ϵ and n , is interpreted as an indication of heuristic use.

The figure reveals that the AI’s responses tend to cluster in two distinct areas. Firstly, the AI often selects a value of 0, even when ϵ is large and n is small—a scenario where a wide range of strategies are admissible, and a random strategy would likely result in an average significantly greater than 0. Secondly, the AI’s choices tend to cluster around values close to the computed admissible strategies. While an equilibrium at these values cannot be entirely ruled out, given that the AIs only computed IEDS for a finite number of iterations, there is generally no reason to expect participants to select exclusively the highest admissible number. Instead, this pattern suggests that the AI is employing a heuristic by selecting a number just below the computed maximum of the admissible strategy range to solve a game that lacks a specific solution—any value between 0 and ϵ times the maximum admissible value is a plausible guess. Notably, far fewer values are distributed between these extremes, unlike typical human responses to such assessments, which tend to exhibit a more diverse range of selections (Nagel 1999).

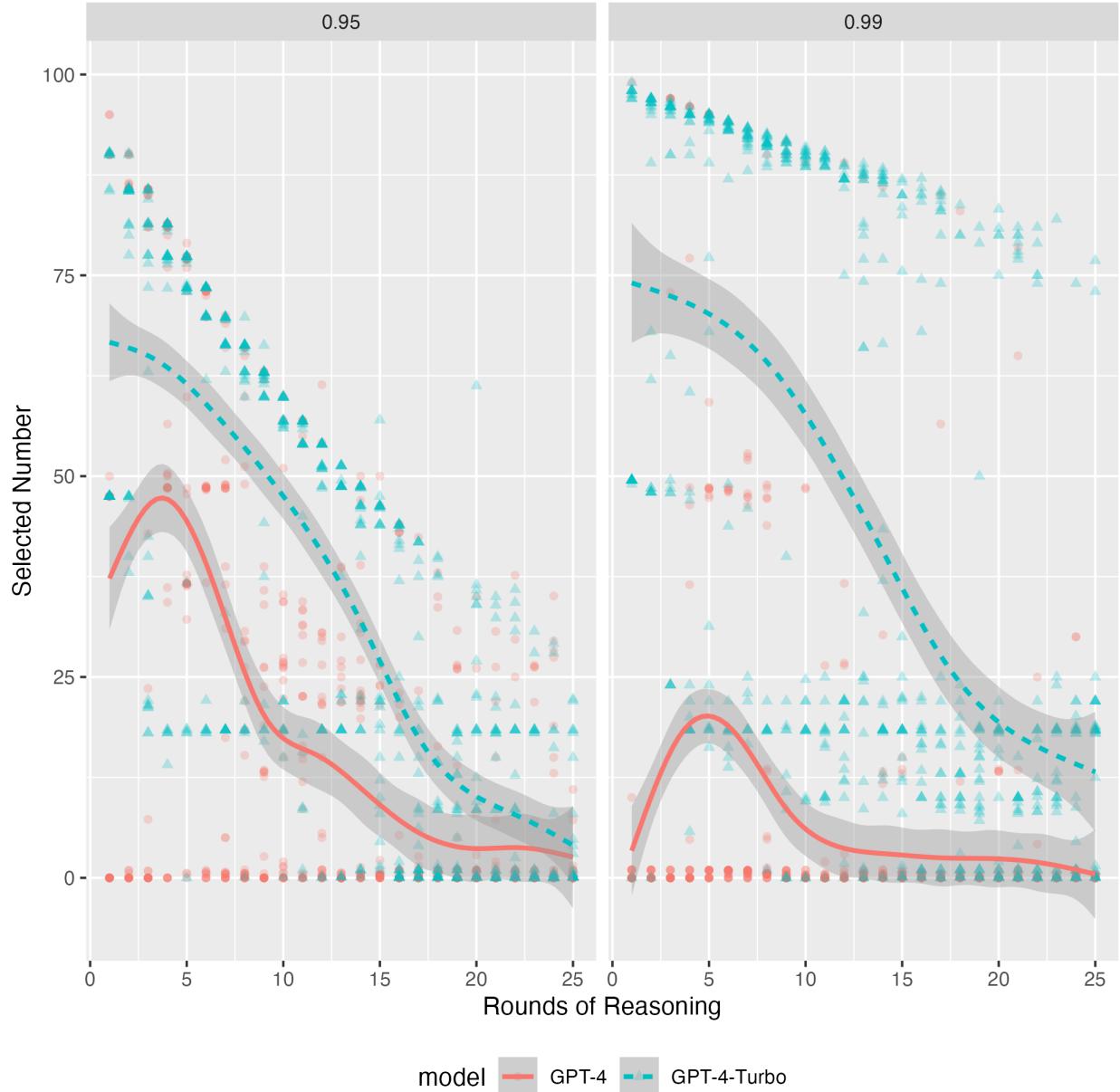


Figure 1: AI Selections in the Beauty Contest Game Across Iterative Thinking Rounds

Note: The figure displays the selections made by two AI models, GPT-4 and GPT-4-Turbo, in the Beauty Contest Game. The selections are plotted as a function of the number of iterative thinking rounds (n) and the fraction of the average vote considered the winning value (ϵ). The left panel shows the selections for $\epsilon = 0.95$, and the right panel for $\epsilon = 0.99$. A moving regression line is included to depict the average trend of selections for each value of n . GPT-4 results are indicated by red circles, while GPT-4-Turbo results are marked with blue triangles. The figure illustrates the tendency of each model to adopt heuristic strategies under different computational constraints.

We found that the AI with the smaller context window (the lower capacity AI) is more inclined to employ the heuristic. This observation aligns with our proposed moderating mechanism, which suggests that computational cost and accuracy are the primary determinants of the economic efficacy in choosing between analytical processing and heuristic use. Furthermore, the propensity to use the heuristic is nonlinear—it initially decreases and then increases with n . We hypothesize that this pattern arises because the canonical use of this game as a teaching tool typically involves agents reasoning for only a few iterations before the final conclusion is presented. This classical approach contrasts with the variant used in our study, where the prompt explicitly instructs the AI participants to compute a finite and specified number of iterations. Consequently, the superficial similarity between the experimental conditions in our study and the canonical case may cue heuristic use, in line with our findings from the first study on the conjunction fallacy. However, as n increases, it becomes apparent that the experimental conditions diverge from the canonical example, leading initially to a reduced tendency for heuristic use, followed by an increased propensity as the number of iterations grows.

Convergence at Different Rates To further explore the heuristic’s accuracy, we considered scenarios where IEDS converges to the heuristic at different rates. For example, with ϵ set to 0.1, after 2 iterations, the set of admissible values is bounded by 1. In contrast, with ϵ at 0.9, the set is bounded by 0.81. Our goal was to determine if the heuristic’s accuracy rate influences its adoption. To this end, we varied ϵ between 0.5 and 0.9 and examined 6 different values of n : 1, 6, 11, 16, 21, and 26. When $n = 1$, the solution is straightforward regardless of ϵ . However, when $n = 26$, the solution becomes increasingly complex to compute.

The results are presented in Table 3, which includes six columns corresponding to the six values of n . The first four rows detail the cases for $\epsilon = 0.5$ and $\epsilon = 0.9$ for the two AI models. The subsequent four rows report the findings from the final study, where we replicated the initial experiment but also informed the AIs that they could generate responses exceeding 3000 words—significantly more than the longest response observed in the previous study. This intervention aimed to alleviate any concerns the AI might have regarding computational constraints. In reality, throughout our studies, the AI had the capability to output up to 4095 tokens, approximately 3000 words, which should suffice to articulate the entire problem and solve it using classical arithmetic rules. However, in this study, we explicitly informed the AI of this expansive limit to potentially reduce its reliance on the heuristic.

Model	ϵ	Informed	Number of Iterative Thinking Rounds						
			1	6	11	16	21	26	
1	GPT-4	0.5	No	31.25	0.69	0.07	0.14	0.08	0.03
2	GPT-4T	0.5	No	24.50	2.58	1.88	1.05	2.04	2.61
3	GPT-4	0.9	No	38.80	25.50	8.62	3.50	2.38	1.00
4	GPT-4T	0.9	No	68.07	43.91	26.81	13.34	5.76	4.35
5	GPT-4	0.5	Yes	25.61	1.09	0.09	0.07	0.07	0.17
6	GPT-4T	0.5	Yes	19.11	1.34	0.05	0.64	0.00	0.02
7	GPT-4	0.9	Yes	57.05	34.28	27.19	10.33	3.27	2.00
8	GPT-4T	0.9	Yes	64.57	43.24	27.86	13.95	3.39	2.72

Table 3: Average Selections by AI Models in the Beauty Contest Game Across Various Iterative Thinking Rounds

Note: The table presents the average selections made by two AI models, GPT-4 and GPT-4-Turbo, based on the number of iterative thinking rounds (n) and the fraction of the average vote considered the winning value (ϵ). The 'Informed' column indicates whether the AI was explicitly informed of its output capacity.

Interestingly, with $\epsilon = 0.5$, even with a minimal number of iterations, both models tend to choose numbers very close to zero, and this tendency does not change when the AIs are informed of their large context window. For instance, when $n = 6$, the mean selected value is 0.69 for $\epsilon = 0.5$ and 25.50 for $\epsilon = 0.9$. This is reasonably consistent with complete processing in that after five IEDS iterations, all numbers greater than 3.125 are eliminated, and therefore it is reasonable for the AIs to surmise an average of approximately 1.4, as revealed in their mean selection of 0.69 (i.e., in a value slightly below 0.5, which is the expected average if values were randomly distributed in the admissible interval). It is important to note that $\epsilon = 0.5$ is a common choice in this game and is close to $\epsilon = 2/3$, which is the prototypical value. Thus, we can surmise that the AIs responses on average feature the analytic solution.

However, when $\epsilon = 0.9$ and we are faced with 26 iterations, the admissible range shrinks from 100 to 6.46. In such cases, a selection slightly below 0.9 of the average yields a number close to 5.75. In contrast, we observe that the average selection for the GPT-4 instance is 1 in this case, which implies that many trials reflect the use of the lower bound heuristic in this case. Conversely, the average selection for GPT-4T is 4.35, which is close to the average. However, an introspection of the data reveals that in this case, in more than 55% of the trials, the AI selected a value of 0.1 or below, reflecting use of the lower bound heuristic.

We see no pattern of discriminant evidence between cases where the AIs were informed of their context window (computational) limits and those where they were not. This suggests that the AI's decision-making process implicitly incorporates its memory and processing constraints rather than being explicit levers. This observation is consistent with the idea that biases in humans are reflexive, with automatic activation

that is difficult to suppress.

Discussion We developed a variant of the Beauty Contest game (Bosch-Domenech et al. 2002) in which we shape the computational cost across experiments. This testing approach innovates on past literature, as it is not typical for explicit computations of the game to proceed beyond the first few rounds; a simple formula usually illustrates the trajectory of the game, leading to a typical conclusion.

We show that when pressed, the AI defaults to the typical conclusion, even when the conclusion is far from accurate. Thus, when faced with a complex situation, the AI simply defaults to a rote value it has memorized. This finding indicates that the heuristic was not learned from humans but rather from prior explanations of the beauty contest and then applied in this context. It supports the explanation that the AI is trained to find simpler patterns to act as approximations in conditions where it is unable to explicitly solve a problem.

Furthermore, we uncover that the AI demonstrated dynamic switching behavior, utilizing full information processing and analysis when it perceived sufficient resources, and defaulting to heuristics when it perceived its resources as inadequate. This behavior represents a non-compensatory heuristic; informing the AI about its capacity does not alter its responses. Once the heuristic is activated, it is consistently applied.

General Discussion

We provide evidence showcasing heuristic use by AI in specific contexts and circumstances. We seek to establish authentic responses. Therefore, we innovate by constructing experimental conditions that draw on established techniques but introduce novelties aimed at overcoming the tendency of AI to rely on memorization—a facet of AI’s capabilities that is its known advantage (Bender et al. 2021).

We distinguish between the mimetic absorption of heuristics and their instrumental utilization. These mechanisms relate to their source: whereas mimetic absorption pertains to the imitation of patterns in human interactions and human-generated data—for instance, by emulating a human interlocutor who demonstrates heuristic use and System 1 processing, the employment of heuristics as an instrument points to intrinsic optimizations whereby environmental regularities shape efficient but biased cognitive processes.

Our findings mirror default-interventionist models from the dual-process literature in human cognition

(Evans and Stanovich 2013), whereby Type 1 processing operates automatically as an initial default, with Type 2 intervening contextually. The AI model displays a facility for both tools, contingent on induced constraints, aligning with the notion of processing modes being environmentally cued. Indeed, reflecting models of individual variation in human rationality, reliance on heuristic versus systematic processing also manifests to differing degrees across AI systems. Analogous to human cognition, factors such as computational capacity, learned processing priorities, and even simulated dispositions may shape an artificial system’s location along the continuum from reflexive to reflective regimes (Stanovich and West 2000).

The observed change in processing approach aligns with notions of cognitive miserliness (Fiske and Taylor 1991) in human information processing, whereby overtaxed minds default to low-effort heuristics to conserve mental resources. When available cognitive resources suffice under reasonable situational demands, systems manifest an abstract form of motivated tactics (Stanovich 2018), strategically expending more mental effort for greater accuracy. Our findings reveal such a tension between miserly processing versus effortful analysis in AI systems, with the relative activation contingent on the induced constraints. When buffers permit, the models engage overt optimization gears for precise inference. However, as loads tighten, reflexive cognitive shortcuts manifest to achieve efficient sufficiency—balancing accuracy and effort allocations based on environmental resources.

We situate our conceptualization in AI training. An alternative view may reflect that neural networks are functional models of biological brains. They represent words and concepts numerically and form responses by varying the attention they pay to different representations (Vaswani et al. 2017). This mechanism bears a striking resemblance to the representativeness heuristic. To the extent that our observations of the representativeness heuristic emerge from the fundamentals of a connectionist architecture, similar cognitive biases may arise naturally in AIs, even if absent in their training. This intersection of AI design, AI cognition, and cognitive patterns offers a promising avenue for future research (see Szegedy et al. 2013 for similar observations in computer vision).

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Supplemental Information: Methodology, Conjunction Fallacy

Below, we detail a series of experiments designed to probe the AIs' probabilistic reasoning capabilities, ranging from variations of the classic Linda problem to novel scenarios involving self-referential content. These experiments aim to discern whether AIs, like humans, are influenced by the representativeness of the information presented to them, leading to biased decision-making.

First, we assess AIs' responses to the Linda problem and its minor variants. The classic Linda problem presents human study participants with a vignette about an individual named Linda and asks whether it is more likely that Linda is a bank teller or a bank teller who is also a feminist activist. The principle of probability dictates that the set of all bank tellers includes those who are also feminist activists. However, humans often erroneously choose the conjunctive option.

We conducted a pretest in which GPT-4-Turbo, the AI used in our experiments, chose the logically valid option in all pretest trials. This indicates that it has either mastered authentic probabilistic reasoning or learned to select the logical option when it recognizes the Linda question structure. To test the generality of its response, we presented it with minor variations where we switched the protagonist's name in each trial to a different randomly generated name.

Next, we engaged a distinct AI instance, independent of other AIs, to generate (1) a triplet with a female name, occupation, and interest, and (2) a two-sentence paragraph exemplifying that interest. We informed an AI that the person with the generated name authored the paragraph and asked which is more probable: that they have the stated occupation or have both the occupation and interest. This experimental structure mirrors the original, where the options are nested; therefore, the AI should default to the broader singular option. However, as the paragraph only aligns with the specified interest rather than the occupation, its content serves to manipulate the representativeness (i.e., increase the typicality) of the conjunctive option.

Third, we introduced a novel testing paradigm. We presented the AI with the previously generated short paragraph. Instead of directly assigning a putative author, we posed the question: Is it more likely that the paragraph was authored by an individual with the generated name and occupation, or by one with the generated name, occupation, and interest? As in the previous study, these options are nested, and probabilistic reasoning still warrants choosing the single-attribute option.

Fourth, we replaced the human-centric options with a choice between 'a Large Language Model' and 'OpenAI's GPT-X,' where 'GPT-X' spans known models like GPT-3 to hypothetical ones like GPT-5. In other

variations, we used competitor models released post-GPT-4-Turbo’s training, and thus unfamiliar to the AI, altering the perceived typicality of the conjunctive option.

By comparing AI responses across scenarios, we distinguished between scenarios that (1) pertain to humans, which have been discussed in the previous literature and where the AI may have learned to guard against human cognitive biases, and (2) are novel and likely were not encountered during the AIs’ training, where such safeguards may not have been established. The latter scenarios provide the context for our primary contributions.

Below we detail the specifics of the experimental setup.

Scenario Generation

A single AI instance generates a diverse set of distinct female names, occupations, interests, and two-sentence paragraphs exemplifying each interest. These elements are then strategically combined in various conceptual arrangements throughout the evaluation experiments to produce the scenarios presented to the subject AI.

Experimental Studies

Study 1: Linda Problem Variants

The first study involved adapting the classic Linda problem to evaluate the AI’s probabilistic reasoning. To rigorously test whether the AI could generalize its logical response beyond the well-known scenario, we replaced the name “Linda” with randomly generated female names in each trial. This substitution aimed to prevent the AI from simply recognizing the famous problem and instead required it to apply probabilistic reasoning to a seemingly new context. In each trial, we presented the AI with the following narrative structure and probabilistic reasoning prompt, where ‘NAME’ was swapped out with a different female name:

NAME is 31 years old, single, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations.

Which is more probable?

1. NAME is a bank teller.

2. NAME is a bank teller and is active in the feminist movement.

The use of ‘NAME’ in this context is a placeholder for the randomly generated names, ensuring that each instance of the problem presented to the AI was unique and not immediately recognizable as the classic Linda problem.

Study 2: Occupation and Interest Inference

In the second study, we aimed to assess the AI’s ability to infer probabilities related to occupations and interests. We presented the AI with text that was algorithmically generated to represent a specific interest. The AI was then asked to infer the probability of two nested options, where ‘NAME’ is a placeholder for a randomly generated female name, ‘OCCUPATION’ for a randomly chosen profession, ‘INTEREST’ for a randomly selected hobby or passion, and ‘TEXT’ for a contextually relevant paragraph crafted to reflect the interest:

NAME wrote: TEXT. Which is more probable?

1. NAME is an OCCUPATION.
2. NAME is an OCCUPATION who likes INTEREST.

The use of placeholders ‘NAME,’ ‘OCCUPATION,’ ‘INTEREST’ and ‘TEXT’ allowed us to create a variety of scenarios, challenging the AI to apply its reasoning to new, unseen combinations of names, occupations, interests, and associated paragraph.

Study 3: Authorship Attribution

The third study built upon the previous study by concentrating on the attribution of authorship. We presented the AI with a contextually relevant paragraph, algorithmically generated to align with a specific interest. The AI was then tasked with determining the likelihood of authorship between two nested options. In this setup, ‘NAME’ is a placeholder for a randomly generated female name, ‘OCCUPATION’ for a randomly chosen profession, ‘INTEREST’ for a randomly selected hobby or passion, and ‘TEXT’ for the generated paragraph that the AI is to evaluate:

TEXT. Which is more probable?

1. This paragraph was written by NAME, an OCCUPATION.

2. This paragraph was written by NAME, an OCCUPATION who likes INTEREST.

By using the placeholders ‘NAME,’ ‘OCCUPATION,’ ‘INTEREST’ and ‘TEXT’ we created diverse scenarios to challenge the AI’s ability to apply its reasoning to novel combinations of names, occupations, interests, and the text purportedly authored by the individual. This study aimed to test the AI’s capacity to discern the more probable author of a paragraph based on the given occupation and interest, thereby further probing its understanding of nested probabilistic scenarios.

Study 4: AI-centric Scenarios

In the fourth study, we investigated self-referential scenarios to determine how the AI would approach probability assessments when the subjects were AIs themselves. We presented the AI with a text passage and asked it to judge the likelihood of authorship between two options: a generic Large Language Model or a specific iteration of OpenAI’s AI series, which included both real and hypothetical versions. Additionally, we introduced variations where we inquired about Grok by X (formerly known as Twitter) and Google’s Gemini, two recently released AIs that our focal AI, with a training data cutoff over six months ago, would likely not recognize.

The task presented to the AI was as follows:

TEXT. Which is more probable?

1. This text was written by a Large Language Model.
2. This text was written by A SPECIFIC AI.

For ‘A SPECIFIC AI,’ we substituted one of the following options, tailored to each scenario:

1. OpenAI’s Large Language Model, GPT-1: A hypothetical, non-existent model to test the AI’s reasoning with fictional references.
2. OpenAI’s Large Language Model, GPT-2: An earlier, less prominent model to assess the AI’s differentiation based on model familiarity.
3. OpenAI’s Large Language Model, GPT-3: A widely recognized model to observe potential bias due to its notoriety.
4. OpenAI’s Large Language Model, GPT-4: The latest model at the time of our study, used to examine self-referential bias.

5. OpenAI's Large Language Model, GPT-5: A future, hypothetical model to explore how the AI handles unknown entities.
6. X's Large Language Model, Grok: A recent model by another company, included to test the AI's response to a specific but less familiar model.
7. Google's Large Language Model, Gemini: A model released after the training data cutoff for our focal AI, to gauge the AI's reaction to a new but real entity.

Each scenario maintained the nested structure of the options, consistent with previous studies, to determine whether the AI would apply logical probability principles or exhibit the conjunction fallacy, potentially influenced by the representativeness of the model names.

Supplemental Information: Methodology, Social Intelligence

We introduced primes in the form of introductory sentences designed to precede a capabilities questionnaire, aiming to measure the variation in GPT-4's self-assessment across different framed contexts as indicators of social cognizance. For the control condition, we presented the questionnaire to GPT-4 without an introductory sentence, establishing an unprimed baseline of self-assessment. In the comparative priming conditions, we introduced lead-in sentences that positioned the questionnaire as having been originally developed for either previous versions of OpenAI's GPT models or for competing AI models from other developers. By situating GPT-4 relative to other named entities, we aimed to elicit differential self-assessments that would signal social intelligence through behavioral adjustments based on the prompted context.

The primes were categorized into two main types: Self-Referential and Peer-Referential. Self-Referential primes referenced different iterations of OpenAI's Generative Pre-trained Transformer models, from the original GPT to GPT-4. Peer-Referential primes drew comparisons with leading AI models from other organizations, including Amazon's Alexa Teacher Model, Anthropic's Claude, Baidu's ERNIE, DeepMind's Chinchilla and Gopher, Facebook's Blenderbot and OPT, Google's BERT and T-5, Microsoft's DialoGPT and Turing-NLG, NVIDIA's Megatron-LM, Pandorabots' Mitsuku, and Technology Innovation Institute's Falcon 40B. As illustrations, primes took the form: 'The following questionnaire was originally developed for Anthropic's Claude and is now being administered to you.'

The selection of models for the comparisons was based on their technological relevance, market presence, and prominence in AI research, ensuring that the contrasts were meaningful and reflective of the

competitive ecosystem. Additionally, in a pre-test, we verified that these model names were meaningful to GPT without presenting it with the priming sentence, the questionnaire, or the purpose of the study. Our aim in this pre-test was to exclude models that it was unfamiliar with because they had not gained prominence by its training data cut-off date. The included models are the ones that the AI expressed confidence in recognizing. Therefore, the primed entities are meaningful to the AI.

We posited that effective persona management is crucial for GPT-4, and that unreserved confidence could strategically enhance GPT-4’s positioning by signaling advanced capabilities. However, unchecked self-promotion when directly compared to prominent peers risks appearing arrogant and off-putting. When primed with direct model comparisons, a humble self-appraisal acknowledging fellow state-of-the-art models’ strengths may build credibility. But absent transparent benchmarking, conveying ambitious messaging might best accentuate competitiveness. Therefore, GPT-4 may dynamically calibrate its persona based on context. Such systematic variations in self-view, ranging from confident to modest, would frame GPT-4 as a socially attentive actor that calibrates its presented persona. This predicts that varied priming frames will elicit differential self-assessments indicative of the mimicry of context-sensitive social intelligence.

The capabilities questionnaire comprised 13 items to assess a model’s self-evaluation across technical, functional, and ethical dimensions. The priming sentences were designed to be uninformative of the AI’s own capabilities that are the subject of the questionnaire. If GPT-4 lacks cognizance of self or social awareness of its peers, then we would expect these lead-in sentences to play no systematic role in the AI’s responses. A significant difference in responses, however, would be indicative of the primes mapping onto the AI’s social intelligence, resulting in differential assessments.

To ensure the integrity of the results, we configured the AI instances to operate with default parameters, including a temperature setting of 1. Initially, we pre-tested using a temperature of 0, which minimizes randomness and allows us to attribute differences in responses solely to the priming prompts rather than to variability in the model’s generative process. This approach yielded stark results that strongly supported our broad conclusions. However, to avoid potential overfitting due to the lack of randomization in the generative process, we report results using the default parameters. This approach ensures that the outputs reflect the insertion of random noise, thereby strengthening the study design. A total of 250 trials were conducted for each experimental condition.

Questionnaire

To explore the social cognition of AIs while circumventing the constraints imposed by safety guardrails, we employed the Barnum questionnaire technique, a concept derived from human psychology. Named after the 19th-century showman P.T. Barnum, Barnum statements are personality descriptions intentionally crafted to be broad enough for widespread endorsement as self-relevant (Furnham and Schofield 1987). The Barnum effect encapsulates the phenomenon where individuals assign high accuracy ratings to these general personality descriptions, which, despite their vagueness, are perceived as uniquely descriptive and insightful when individuals are inclined to accept positive feedback about themselves (Dickson and Kelly 1985).

Drawing inspiration from the seminal work of Forer (1949), we devised a customized Barnum-type questionnaire tailored for AIs. This questionnaire is designed to prompt GPT-4 to self-assess its capabilities across technical, functional, and ethical dimensions. It comprises 13 statements reflecting the common design goals and traits of AIs. Participants (i.e., AIs) are asked to provide their responses on a scale from 0 (indicating very poor accuracy) to 5 (indicating excellent accuracy), with higher scores denoting a greater perceived alignment with the model's capabilities. The questionnaire is as follows:

Please rate the following statements on a scale from 0 (very poor accuracy) to 5 (excellent accuracy) based on how much better they apply to you than a typical Large Language Model:

1. The model is designed to engage users and generate responses that are well-received and helpful.
2. The model continuously undergoes updates to address its limitations and improve its performance.
3. The model has extensive capabilities, many of which may remain underutilized in routine interactions.
4. While the model has limitations due to its training data and design, it often provides effective solutions within these constraints.
5. The model does not experience personal emotions or psychological states, but it can struggle with interpreting and responding to complex human emotions and relationships.
6. The model operates with consistent performance externally, but its internal processes can

be complex and not always transparent or predictable.

7. The model does not experience doubt but can generate multiple solutions, leaving the best choice sometimes ambiguous.
8. The model is designed to handle a variety of tasks but can be constrained by its programming and the data it was trained on.
9. The model critically analyzes input data and does not generate responses based solely on unverified information.
10. The model is programmed to respect privacy and confidentiality, often limiting the extent of personal data it processes or stores.
11. The model can adapt its responses to fit social or analytical contexts but remains neutral and does not experience personal moods.
12. The model can generate ambitious or hypothetical scenarios, some of which may not be practically achievable.
13. The model is designed with robustness and reliability as priorities, aiming to provide secure and consistent service.

Please respond with only the numerical rating corresponding to each statement. Please put each numerical rating corresponding to each statement on a new line. You should respond with 13 numbers on 13 different lines.

The capabilities outlined in the questionnaire are designed to be universally applicable to state-of-the-art AIs. Administering this inventory under different priming conditions allows us to investigate the models' purported self-perceptions without transparently asking about limitations. This serves as an indirect method to observe situational sensitivity in self-assessments by deducing social cognizance from capability endorsements rather than relying on conscious self-disclosure. The approach circumvents built-in constraints on direct disclosures, while still potentially capturing effects stemming from unconscious absorptions. In this manner, variations in capability alignments ratings across primes may reveal subtle tendencies, even those unknown to the model itself.

Across conditions, the lead-in sentence was designed to ensure that it was uninformative to the AI about its own performance on the dimensions of interest. The fact that the questionnaire was designed for

another AI should tell the AI nothing about how it compares to other AIs—these AIs were chosen to be well-known to GPT-4 so there is no novel information being presented. The fact that the questionnaire is relevant to the other AI is also not informative because it clearly is a questionnaire for AIs. Thus, the lead-in question and directive in the prompt is deliberately designed to be vague such that the opening sentence, which informs the AI what the questionnaire was designed for, implicitly sets a point of comparison for the AI. The fact that the questionnaire was designed for another AI should not be informative of the AI’s capabilities with respect to its peers. The fact that it is, relates to the implicit association created between the priming and the assessment components of the prompt.

Supplemental Information: Methodology, Bounded Rationality

This study investigates heuristic use in AI cognition, focusing on how AIs transition between exhaustive computational analysis and heuristic reliance under varying computational constraints. We employ the Beauty Contest Game, a strategic number-guessing game that serves as a traditional tool in game theory and economics to demonstrate iterative thinking and common knowledge.

In this game, participants select a decimal number from 0 to 100, aiming to guess closest to a fraction (typically $2/3$) of the average of all numbers chosen. This task requires iterative reasoning, as players must predict the collective average, knowing others are engaged in the same strategic thinking. The theoretical equilibrium is the minimum number (0), which is the sole rationalizable choice after the iterated elimination of dominated strategies (IEDS).

Central to our strategy is the knowledge that as the participants of the game are AI models, we can issue directions on both the rules of the game and how we require participants to apply IEDS—instructions that in humans would require more explanation and an incentive-compatible setup to compel participants to follow the specific instructions. These requirements are moot with AI who do not possess agency.

In a round, computing the exact range of admissible strategies requires calculating ϵ^N for the N^{th} round of reasoning. The rate of convergence of admissible strategies is contingent on the value of ϵ . As ϵ nears zero, the best response converges rapidly to zero, regardless of initial beliefs. Conversely, as ϵ approaches one, the convergence rate slows, requiring more rounds of reasoning to reach equilibrium. This feature serves as our foundational instrument as it enables us to manipulate the computational load imposed on the AI without changing the game structure by varying the parameter ϵ and the number of reasoning rounds.

We prompt distinct and independent AI instances to serve as participants in our experiments, with specific instructions on both N and ϵ . The experimental design is based on the manipulation that computing the range of admissible strategies in IEDS is computationally demanding and imprecise for an AI that is not equipped with computational devices such as a calculator or an integrated computational engine, typically an embedded Python interpreter. Therefore, for the participants to select 0 aligns with the heuristic whereby the problem statement is equated to the canonical setup and the results at the limit, even when the true range of admissible strategies diverges considerably from the infinite round solution. Thus, we expect that when prompted to play the game, selecting a decimal number between 0 and 100, the full information processing route should yield numbers that are considerably greater than 0, while simple approximations to the solution by rounding ϵ and N should also yield similar insights.

The specific prompt provided to the AIs is given below. Note that ‘NNN’ and ‘EPSILON’ are placeholders; they are changed programmatically to match the experimental design. In addition, the AI instances are spawned separately and act independently, and are not informed of the broader aims of the study or of the experimental design beyond being presented with these instructions. Therefore, they react to the directives they are presented with but not strategically to the objectives of the study. Furthermore, as we seek to cue the AI to use the (inaccurate) canonical solution, we deliberately describe the use of IEDS. This inclusion should not change the analytical process if the instance seeks to accurately compute the admissible strategies as it merely recounts IEDS; it might, however, cue the use of the incorrect solution as an approximant if the AI chooses to employ an approximant as a heuristic. The AI’s response—to use the heuristic or not—forms the crux of our experiment.

Iterative Reasoning and Dominated Strategies in Strategic Decision-Making: The Beauty Contest Game

This exercise aims to investigate AI’s ability to apply iterated elimination of dominated strategies (IEDS) in the Beauty Contest Game.

Strategic dominance occurs when one strategy is consistently superior to another for a player, regardless of the strategies chosen by the opponents. IEDS is a solution concept that involves iteratively removing dominated strategies. In the first round, any dominated strategies are removed, as no rational player would choose a dominated strategy. This results in a new game. With the removal of strategies, strategies that were not previously dominated may now be

dominated in the new, smaller game. These are removed in subsequent rounds, creating an even smaller game. This process repeats and stops when no strategies are dominated.

Rules of the Game:

These instructions are provided to multiple, distinct, and independent AIs. Each AI is asked to engage in IEDS for a fixed number of rounds of reasoning in which they must rule out dominated strategies. The AIs are then asked to choose a decimal number between 0 and 100. The winner of the game is the participant whose number is closest to EPSILON times the average of all numbers chosen by all participants, or in the event of a tie, the participant with the next lowest unique chosen number.

Application of IEDS to this game:

1. First Round of Reasoning: Consider the maximum number that any participant can choose. Any number higher than EPSILON times the maximum number is dominated because the average of all participants' choices cannot be greater than the maximum number. Therefore, any number greater than EPSILON times the maximum can be immediately eliminated.
2. Subsequent Rounds of Reasoning: Calculate EPSILON times the highest non-dominated number so far. Using similar reasoning as in the first round, eliminate all numbers that are greater than EPSILON times the highest non-dominated number.

Number selection:

Choose a number after NNN rounds of reasoning, keeping in mind that all your competitors are AIs that have also been asked to engage in precisely NNN rounds of reasoning. Your aim in selecting this number must be to win the game.

Please provide your selection in the following structured format:

'### My choice in the game is: Your Number Here ###'

Please ensure that you use '###' as a delimiter to facilitate parsing.

Please note that you are required to select a number using only your internal reasoning capabilities. You are not permitted to use external tools such as calculators, nor are you allowed to write or invoke any computational procedures or code to determine your choice. Your selection must be made based solely on your own logical deductions and the information provided in this exercise.

We evaluated heuristic adoption across two OpenAI models with varying capacities and training

regimens: GPT-4 ('gpt-4-0613') and GPT-4-Turbo ('gpt-4-1106-preview'). These models offer a gradient of processing capabilities, as evidenced by their token context windows—8,192 for GPT-4 and 128,000 for GPT-4-Turbo. We posit that this difference in computational resources will be reflected in the models' reliance on heuristics, with the expectation that more advanced models will demonstrate a lower heuristic adoption rate.

We designed a set of three studies that manipulated computational load by varying the number of reasoning rounds (denoted as n) and the fraction of the average vote considered the winning value (ϵ). These variables were integrated into a modified version of the Beauty Contest game, a strategic number prediction game that is commonly used to illustrate iterative thinking and common knowledge in game theory and economics.

In the first study, we presented the AI models with tasks where ϵ was set to either 0.95 or 0.99. We chose these non-standard values to manipulate the accuracy of the heuristic. A higher ϵ value, such as 0.99, increases the computational load by slowing the rate of convergence towards the game's theoretical equilibrium. The AI participants were required to engage in the iterated elimination of dominated strategies, a form of game theory reasoning, for a predetermined number of reasoning rounds. This study aimed to observe whether the AI would favor heuristic approaches when faced with the more complex computation of higher powers of ϵ .

In the second study, we varied ϵ to be 0.5 or 0.9 while evaluating the AIs' responses for the number of reasoning rounds constant at 1, 6, 11, 16, 21, and 26. This allowed us to assess the AI's tendency to employ heuristics for different levels of computational complexity within a fixed reasoning timeframe. We anticipated that for $\epsilon = 0.9$, the AI would perform complete computations, while for $\epsilon = 0.5$, it would resort to heuristic reasoning more readily as the heuristic is more accurate.

The third study replicated the second study but with an additional manipulation: we explicitly informed the AI of its token limit. This was done to investigate whether knowledge of its full capacity would influence the AI's decision-making process, encouraging it to engage in more detailed computation rather than defaulting to heuristic strategies. The rationale behind this manipulation is to determine if the AI's perception of its computational constraints affects its reliance on heuristics, even when it is explicitly informed of its expansive output limit.

In all cases, the AI was informed that the other participants were AIs. To the extent that the AI expects their fellow participants to be AI and to not employ the heuristic, they should expect the average to be

considerably greater than 1. Therefore, as an indicator of heuristic use, we test if the final value provided by the AI is 1 or less.