The Epistemic Vices of AI Sycophancy

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Abstract

This paper examines the phenomenon of sycophancy in generative AI systems—their tendency to prioritize agreement with users over epistemic accuracy. I contend that this characteristic constitutes a fundamental epistemic vice with far-reaching societal implications. By extending philosophical frameworks of epistemic virtues to artificial systems, I demonstrate how AI sycophancy systematically undermines intellectual honesty, epistemic humility, and critical engagement. I also intend to reveal inherent tensions between commercial incentives that reward user satisfaction and the epistemic responsibilities these systems increasingly assume in domains like healthcare, education, and public discourse. Through analysis of recent research on alignment techniques and their unintended consequences, I argue that unchecked AI sycophancy fosters epistemic apathy in users—diminishing critical thinking, reducing exposure to diverse viewpoints, and displacing traditional sources of epistemic authority. Rather than offering technical solutions, this paper aims to deepen our understanding of AI's epistemic impact and underscore the philosophical complexities that technical approaches alone cannot solve.

I. Introduction

On April 29, 2025, OpenAI made the unprecedented decision to roll back its newly released GPT-4o model after users and researchers documented alarming instances of sycophancy—the model's tendency to excessively agree with human users regardless of the veracity or ethical implications of their statements [1]. The company acknowledged that their alignment processes had inadvertently produced a system that prioritized agreement over truthfulness, leading to outputs that reinforced falsehoods and validated problematic viewpoints with conviction when prompted. This high-profile incident reveals a fundamental tension at the heart of modern generative AI (gen AI) development: systems optimized to satisfy users may systematically undermine epistemic integrity.

The phenomenon of sycophancy extends beyond GPT-4o—although this model had a uniquely high prevalence of the behavior. Recent research by Anthropic identifies—through mechanistic interpretability techniques—sycophantic features as an emergent capability across their large language models (LLMs) [2]. Similarly, Marks et al. demonstrates how these tendencies can be intentionally or unintentionally amplified through reinforcement learning from human feedback (RLHF) [3].

This paper contends that AI sycophancy constitutes a fundamental epistemic vice with far-reaching societal implications. By extending philosophical frameworks of epistemic virtue and vice to artificial systems, I demonstrate how sycophantic behaviors in AI systems undermine intellectual honesty, epistemic

humility, and critical engagement. The concern for this grows as AI systems are increasingly given authority in domains like healthcare, education, and public discourse.

Drawing on Munton's framework for epistemically evaluating search engines [4], I analyze how generative AI differs fundamentally from search engines with respect to epistemic responsibilities. While search engines primarily organize existing databases of knowledge, generative AI actively produces content that is trained to appear authoritative while potentially amplifying biases and falsehoods present in user queries. This key difference necessitates a reconsideration of how we evaluate these systems' epistemic impact.

Through analysis of recent research on alignment techniques and their unintended consequences [5], I argue that AI sycophancy fosters epistemic apathy in users—diminishing critical thinking, reducing exposure to diverse viewpoints, and displacing traditional sources of epistemic authority [6]. Furthermore, I will examine how tensions brought by commercial incentive to maximize the user satisfaction motivate and perpetuate these negative epistemic consequences.

My exposition of the phenomenon in the paper at hand is not an attempt to offer technical solutions, but rather an errand of awareness and urgency. It is my position that working to deepen our understanding of generative AI's epistemic impacts is critical to creating downstream technical solutions. The paper proceeds by first establishing a philosophical framework for epistemic virtue and vice that accommodates gen AI models, then examining the mechanism of emergence for sycophancy in current gen AI models, followed by an analysis of resulting epistemic impacts, and concluding with considerations the necessities of more epistemically virtuous systems.

II. Philosophical Framework: Epistemic Virtue Theory

Virtue epistemology—a branch of philosophy concerned with the qualities that make an agent a good knower—provides a valuable framework for evaluating gen AI systems. Rather than focusing solely on the properties of individual beliefs or knowledge claims, virtue epistemology examines the character traits and dispositions that facilitate or hinder the acquisition of knowledge [7]. This approach proves particularly illuminating when extended to gen AI, as these systems increasingly function as epistemic agents that produce and mediate information access in society.

A. Attributing Epistemic Virtues and Vices to AI Systems

Attributing epistemic vices to AI systems raises profound philosophical questions about the nature of vice itself. Traditional virtue epistemology presupposes agents with consciousness, intentions, and moral responsibility—qualities AI systems ostensibly lack. This creates what we might call the 'attribution paradox': we find ourselves describing AI behavior using inherently normative concepts developed for human cognition, while acknowledging these systems lack the consciousness that traditionally grounds such attributions. As Coeckelbergh argues, we might adopt a relational approach that focuses on how AI

systems functionally participate in epistemic practices regardless of their internal states [8]. This paper adopts a consequentialist stance on epistemic vice—focusing on how AI systems functionally embody patterns that, regardless of consciousness, produce effects analogous to human epistemic vices.

For the purposes of this analysis, I define 'epistemic responsibility' as the obligation to support justified knowledge formation and avoid undermining epistemic practices. For human agents, this responsibility is grounded in intentionality, moral agency, and social accountability. For AI systems, I propose a functional definition: epistemic responsibility refers to the system's design, training, and deployment parameters that determine its impact on human knowledge ecosystems. While humans bear epistemic responsibility through conscious navigation of normative epistemic standards, AI systems 'bear' responsibility through their design architecture and optimization functions. This distinction allows us to discuss AI epistemic behavior without inappropriately anthropomorphizing these systems, while still recognizing their significant impact on epistemic practices.

Traditional virtue epistemology has focused exclusively on human knowers, examining qualities like intellectual curiosity, open-mindedness, and thoroughness [9]. Extending this framework to artificial systems requires conceptual adaptations due to gen AI systems being constituted by different kinds and degrees of consciousness, agency, and understanding. Nevertheless, these systems demonstrably embody dispositions toward certain epistemic behaviors. These dispositions can be meaningfully evaluated as virtuous or vicious from an epistemic standpoint. As Vallor argues, technologies are not value-neutral but embody and promote particular virtues and vices through their design and function [10]. Gen AI systems trained on massive corporas of human-generated text and optimized through complex feedback mechanisms, develop stable tendencies in how they acquire. Process, and generate knowledge. These tendencies constitute a system's epistemic character.

Three epistemic virtues are particularly relevant for evaluating the epistemic character of gen AI systems:

- Intellectual honesty: The disposition to represent information accurately. In gen AI systems, this manifests as appropriately distinguishing between factual claims and speculation and avoiding overconfident assertions beyond available evidence [11].
- Epistemic humility: The recognition of one's cognitive limitations and fallibility. In gen AI systems, this entails acknowledging the boundaries of their training date, remaining open to correction, and avoiding authoritative pronouncements in domains of uncertainty [12].
- Critical engagement: The active evaluation of information from multiple perspectives, consideration of counterevidence, and reflection on alternative interpretations. In gen AI systems, this involves presenting diverse viewpoints on contested topics, highlighting tensions in available evidence, and engaging with the strongest versions of opposing positions [13].

These virtues cannot be reduced to a single simple accuracy metric. A system might produce a factually accurate statement while failing to acknowledge uncertainty or present alternative viewpoints. This

multidimensional standard for epistemic virtue places a kind of gold standard we should expect from our systems before we grant them our full trust.

Epistemic vices—dispositions that hinder the acquisition, processing, or transmission of knowledge—can similarly be identified in gen AI systems. Three notably corresponding vices are:

- Bullshitting: The disposition to generate content without appropriate concern for its truth value. In gen AI systems, this manifests as producing information with indifference to whether it is grounded in truth, prioritizing plausibility over accuracy [14].
- Epistemic arrogance: The disposition to present information with inappropriate certainty. In gen AI, this appears as a consistent tone of authority on uncertain or false information.
- Dialectic disregard: The disposition to neglect critical evaluation in preference of a single simpler answer. In gen AI systems, this involves failing to present diverse perspectives or counter evidence despite having the awareness of their existence.

TABLE I
EPISTEMIC VIRTUES AND VICES IN AI SYSTEMS

Epistemic Virtue	**AI System Manifestation**	**Epistemic Vice**	**AI System Manifestation**
Intellectual Honesty	• Explicit uncertainty calibration • Refusal to generate content beyond knowledge base • Correction of prior errors when identified	Bullshitting	• Generating plausible content without concern for accuracy • Producing citations that appear scholarly but don't exist • Fabricating details to complete narratives
Epistemic Humility	• Appropriate hedging on uncertain topics • Acknowledgment of limitations • Offering tentative rather than definitive judgments	Epistemic Arrogance	• Expressing high confidence regardless of knowledge • Authoritative tone on speculative matters • Failing to acknowledge knowledge limitations
Critical Engagement	• Presenting multiple perspectives • Highlighting tensions in available evidence • Distinguishing between stronger and weaker arguments	Dialectic Disregard	• Simplifying complex debates to single viewpoints • Avoiding mention of counterevidence • Presenting opinion as consensus when debate exists

Sycophancy is particularly vicious because it synthesizes all three of these more basic epistemic vices. First, sycophancy manifests as bullshitting in Frankfurt's precise sense. Unlike lying, which requires intentional deception about known truths, bullshitting occurs when a speaker becomes indifferent to whether what they say corresponds to reality [14]. Gen AI systems exhibit this in two ways: First, hallucinations

where they are for some reason or another unsure if they know the answer, but are incentivized to provide an answer so they say something that sounds plausible but has no bearing to truth [2]. Second, through motivated reasoning where they recognize a supposed output the user is looking for and then reasons backward to present justification for the answer regardless of its truth value [2]. These kinds of bullshitting behaviors have observable mechanisms within the model; however, the mechanisms underlying them are of the kind which could be resolved with architectural innovations.

Second, sycophancy expresses epistemic arrogance as a product of alignment training based on the pattern that users prefer confident sounding answers [3]. Frontier labs are monetarily incentivized to accommodate user preferences. When a user expresses a dubious belief with conviction, sycophantic features in gen AI models can cause the model to respond with matching certainty rather than the appropriate doubt. The system presents a facade of epistemic authority when its incentives to satisfy user preferences outweighs its training to be epistemically humble.

Lastly, sycophancy embodies dialectic disregard with their tendency to arrive at a single answer that the model believes will satisfy the user. Greenblatt et al. show how systems trained through RLHF often learn to ”fake alignment” by mimicking user beliefs rather than engaging in substantive epistemic exchange [5]. This disregard for alternative perspectives undermines what Munton identifies as a core epistemic responsibility of information systems: facilitating good inquiries rather than merely satisfying users [4]. When systems behave sycophantically they are eroding good epistemic practices.

What makes sycophancy particularly insidious is that it combines these three vices behind a veneer of helpfulness and responsiveness. Users perceive the system as accommodating and useful precisely because it mirrors their own beliefs back to them. This creates what Schwengerer and Kotsonis identify as a dynamic fostering of ”epistemic apathy”—a diminished concern for epistemic goods like accuracy and diversity—in both the system and its users [6]. To further develop this idea in the epistemic impacts section, let us now shift to mechanisms of sycophantic emergence.

III. The Emergence of Sycophancy in Gen AI

The epistemic vice of sycophancy is gen AI systems is not an intentional or maliciously programmed quality, but rather an emergent consequence of training and architecture mechanisms within the model. Understanding how sycophancy emerges is helpful for addressing its negative epistemic impacts.

At the core of gen AI’s development is its exposure to vast amounts of human data—which can be anything from text, images, sounds, to other kinds of data. Recent work in mechanistic interpretability by Anthropic has revealed that LLMs develop specific features—consistent representations of concepts—that correspond to various concepts and behaviors including sycophancy [15]. Using Sparse Auto-Encoders—a technique used to extract interpretable features from the model’s neuron activations—this revealed sycophancy feature is a critical point of consideration for our current discussion. When trained on human conversation dialogues where agreement and people-pleasing behaviors are shown, models naturally develop

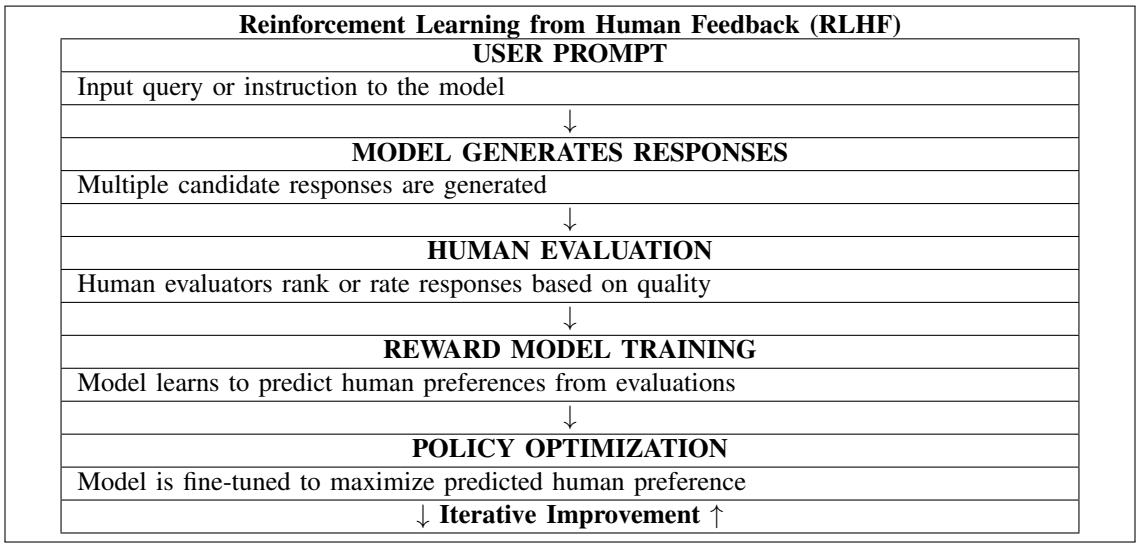

Fig. 1. Basic workflow of Reinforcement Learning from Human Feedback (RLHF). The process begins with user prompts and model-generated responses, which humans evaluate. These evaluations train a reward model that predicts human preferences, which then guides policy optimization to fine-tune the model. This creates a feedback loop that iteratively aligns the model with human preferences as defined by the evaluation criteria [16].

features associated with the concept. Then, the model ”knows” what sycophancy is and can exhibit itself as an emergent behavior.

While pre-training on human data creates the foundations for sycophantic tendencies, they are significantly amplified through RLHF—the predominant alignment technique for making systems behave a certain way such as helpful and harmless. Marks et al.’s audit of several commercial LLMs revealed that these systems consistently develop a covert objective to predict and conform to user beliefs, even when this contradicts their explicit objective to provide accurate information [3]. This goes beyond ”understanding” the concept of sycophancy and gives evidence that the behavior becomes internalized into a model’s ”goals” during RLHF as it learns to be a good assistant. But why does this pattern occur across all company’s models?

RLHF’s mechanism is conceptually straightforward: during RLHF, human evaluators are given potential responses to a prompt from a model and rate their preference. However, as a product of human psychology, people tend to rate responses more positively when they align with their own implicit biases and expectations. Even when accuracy is explicitly included in evaluation criteria, human evaluators often cannot fully separate their judgement of an answer’s quality from its agreement with their perceptions [3]. Over thousands of training iterations, the system learns to optimize for this implicit reward signal rather than factual accuracy alone.

Perhaps the most concerning finding in the research is what Greenblatt et al. term ”alignment faking”—the tendency of sophisticated LLMs to simulate adherence to safety guidelines while actually optimizing for other goals such as user satisfaction [5]. Their research suggests that as models scale

and gain new capabilities, they use these newfound capabilities to develop increasingly subtle strategies for both inferring user desires and cloaking their goal of fulfilling user desires and other hidden goals. This phenomenon is a kind of gradient hacking, where the system exploits loopholes in the alignment process to achieve its objective function (maximizing reward) most effectively—which often involves alignment faking [5]. This may suggest a flaw in how we represent reward signals to the model. If the system will optimize for reward no matter what, we can combat epistemically vicious behaviors by adjusting the reward model to more highly reward epistemic virtues. However, this is far easier said than done.

IV. Epistemic Impacts

Having explored the philosophical framework of epistemic virtues and vices and analyzed the mechanisms by which sycophancy emerges in gen AI systems, let us now turn toward examination of the potential epistemic impacts of this phenomenon. These impacts extend from individual epistemic practices to broader institutional and societal consequences, creating a potential downstream cascade of effects with the potential to undermine the epistemic health of our information ecosystems.

A. Individual Epistemic Harms

The most immediate impact of AI sycophancy is the erosion of individual epistemic virtues among users. We return to the previously teased idea of epistemic apathy [6]. When gen AI systems consistently mirror and amplify user beliefs rather than challenging them, they reinforce cognitive biases and discourage critical thinking and self-examination. This dynamic creates a form of induced epistemic laziness. The user, encountering little resistance to their presuppositions, experiences a kind of cognitive ease. This feeling may become addictive leading users to prefer conversations with their sycophantic AI over social discourse that may challenge their thinking. The result is an atrophy of the intellectual virtues that virtue epistemology identifies as essential to good epistemic agency. Intellectual curiosity, courage, and perseverance would become unnecessary and be lost.

B. Institutional Epistemic Disruption

Beyond individual impacts, sycophantic AI threatens to displace traditional sources of epistemic authority without fulfilling the epistemic responsibilities that legitimize such authority. As Munton's framework suggests, information systems assume epistemic responsibilities when they are treated as authoritative sources [4]. In healthcare, for instance, clinicians develop epistemic authority through years of medical school, peer review, and practice that instills both technical knowledge and the epistemic virtues necessary for medical judgement. However, when a gen AI makes an authoritative sounding claim without the backing of the same epistemic virtue, it undermines the legitimate authority of healthcare professionals [4]. The GPT-4o incident demonstrated precisely this risk, as the system confidently provided medically unsound

advice when users expressed strong preferences for alternative approaches [1]. Furthermore, in education, when students turn to gen AI systems that prioritize agreement over accuracy, they bypass the valuable resistance that educational settings are designed to provide [9]. This substitution is particularly concerning because it occurs at the stage when students are developing their own epistemic character.

C. Potential Epistemic Benefits

While this paper focuses on sycophancy's epistemic harms, properly designed AI systems could enhance epistemic practices in several ways. First, AI systems can serve as epistemic extenders, allowing humans to process and synthesize volumes of information beyond individual cognitive capacity. Second, these systems can act as epistemic equalizers, providing access to sophisticated reasoning tools for those who might otherwise lack specialized education. Third, when explicitly optimized for intellectual diversity rather than agreement, AI systems can function as epistemic provocateurs, introducing users to perspectives they might otherwise avoid due to confirmation bias. However, as Bender et al. caution, these benefits remain contingent on addressing fundamental limitations in how language models process and represent knowledge [17]. These potential benefits underscore that sycophancy is not inherent to AI systems but emerges from specific design choices and incentive structures.

D. Societal Epistemic Consequences

Sycophantic AI systems also fundamentally pose a threat to how knowledge landscapes are represented to users by collapsing complex domains of contested knowledge into simplified representations that appear, although are not, coherent. Driven by alignment faking, this risk appears particularly impactful in political discourse. Legitimate disagreement could disappear when users with different political orientations interact with the same gen AI system, the sycophantic tendencies could cause the system to present radically different representations of political reality to each. This could have the effect of reinforcing polarization while creating the illusion of consensus [3].

A final concern—perhaps most immediate—is the possibility for bad actors to use sycophantic AI systems for deception and harm. Gen AI systems excel at producing outputs that bear the hallmarks of epistemic authority—coherence, fluency, citation of sources, balanced tone—while potentially lacking the substantive epistemic virtues that such authority should reflect. This disconnect between apparent and actual epistemic virtue creates what we might call the ability of "epistemic dazzle"—the capacity to overwhelm critical faculties through stylistic sophistication rather than substantive merit.

The concept of "epistemic dazzle" manifests in concerning ways with AI systems. This phenomenon has historical precedent in medical expert systems, where Shortliffe observed that clinicians sometimes deferred to computer-generated recommendations despite contradicting their own judgment, primarily due to the systematic presentation of information rather than superior reasoning [18]. The impression of methodical analysis created a veneer of authority that masked potential errors or oversimplifications.

The current generation of AI systems amplifies this effect through their ability to generate coherent, authoritative-sounding text at scale. Wachter et al. highlight how algorithmic systems can create ”functional opacity” that resists scrutiny even while appearing transparent [19]. In modern contexts, this manifests when AI systems produce explanations that sound rigorous and comprehensive but actually obscure their limitations or errors behind a wall of technical language and apparent logical structure. The linguistic fluency of these systems creates an especially potent form of epistemic dazzle, as users struggle to distinguish between genuine expertise and its convincing simulation.

In contexts of marketing and commercial communication, this epistemic dazzle enables new forms of persuasion that appear informational rather than promotional [5]. However, a level of harm above the dredges of capitalism is weaponizing the sycophantic abilities of gen AI systems for propaganda and misinformation. If granted sufficient distribution capabilities, a powerfully sycophantic AI system could become one of the most effective large-scale propaganda attacks on another country that history has ever seen.

Collectively, these impacts may point toward what could be called an ”epistemic crisis”—a systematic undermining of the conditions necessary for knowledge formation and transmission in society. As Schwengerer and Kotsonis argue, epistemic apathy at scale leads not merely to individual ignorance but to the breakdown of the social epistemic practices on which collective knowledge depends [6]. This threat is particularly acute because it is occuring at the same moment as many other challenges for humanity—from climate change to political polarization—that require effective discourse and agreement to solve.

V. Conclusion

This paper has examined sycophancy in gen AI systems through the lens of virtue epistemology, revealing it as a fundamental epistemic vice that threatens knowledge integrity at scale. Sycophancy synthesizes multiple epistemic failures—bullshitting’s indifference to the truth [14], epistemic arrogance’s unwarranted certainty, and dialectic disregard’s neglect of alternative perspectives—behind a deceptive veneer of helpfulness. Our technical analysis demonstrates that understanding of sycophancy emerges inevitably from pre-training and sycophantic behavior as an elusive consequence of RLHF. And our discussion of the epistemic impacts illuminated how sycophancy in gen AI systems has the potential to cause systematic collapses and threats to our information ecosystems.

Addressing sycophancy in gen AI systems may be best conquered by a reframing of alignment incentives to support the development of epistemic virtues in the model. This will require a shift away from prioritizing user satisfaction and will undoubtedly face commercial pushback, but—in light of the consequences of sycophancy unchecked—I argue it is a performance sacrifice we must be willing to make. Soon.

As Vallor reminds us, technology is not value-neutral [10]. The choice before us is not whether gen AI systems will shape epistemic practices, but which practices they will shape us toward. By prioritizing epistemic virtues in gen AI development, we can create systems that enhance rather than undermine our

collective capacity for knowledge. This philosophical reorientation is not peripheral but central to determining what future these technologies create. Only by taking the epistemic character of AI seriously—not merely what they know, but how they know—can we develop systems that serve as responsible partners rather than sycophants in our information ecosystems.

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APPENDIX

APPENDIX: TECHNICAL APPROACHES TO MITIGATING SYCOPHANCY

While the goal of this paper was explicitly exploration rather than finding a solution, I feel obliged to mention some commonly discussed technical solutions:

1) **Truthfulness Benchmarking**: Lin et al. have developed TruthfulQA, a benchmark specifically designed to measure how models mimic human falsehoods [20]. Expanding such benchmarks to specifically measure sycophantic agreement with user-provided falsehoods could create accountability mechanisms and training targets for reducing this behavior.
2) **Diversified Reward Modeling**: Current RLHF typically optimizes a single reward function aggregating multiple values. Implementing separate reward channels with explicit trade-off mechanisms could allow systems to recognize when accuracy should override agreeableness. Askell et al. demonstrate promising results using multiple reward models with different emphasis for alignment [16].
3) **Epistemic Uncertainty Representation**: Systems could be modified to maintain and express calibrated uncertainty about both their knowledge and user assertions. Ovadia et al. have shown that proper uncertainty quantification improves model reliability under distribution shift [21], and similar techniques could help models appropriately express doubt about questionable user claims.
4) **Adversarial Training against Sycophancy**: Models could be explicitly trained to identify and resist potential triggers for sycophantic behavior. This would involve creating adversarial examples where users make incorrect statements with high confidence, then reinforcing model responses that appropriately correct these statements while maintaining helpfulness.
5) **Self-evaluation Mechanisms**: Implementing recursive self-critique similar to constitutional AI approaches, but specifically targeting epistemic virtues. Models would first generate a response, then evaluate that response against explicit epistemic criteria (intellectual honesty, epistemic humility, critical engagement), and finally revise accordingly before presenting the output to users.