A rebuttal of two common deflationary stances against LLM cognition

Zak Hussain[1,2], Rui Mata[1], Dirk U. Wulff[2,1]

[1]Faculty of Psychology, University of Basel, Basel, Switzerland
[2]Center for Adaptive Rationality, Max Planck Institute for Human Development, Berlin, Germany

Correspondence: z.hussain@unibas.ch

Abstract

Large language models (LLMs) are arguably the most predictive models of human cognition available. Despite their impressive human-alignment, LLMs are often labeled as "*just* next-token predictors" that purportedly fall short of genuine cognition. We argue that these deflationary claims need further justification. Drawing on prominent cognitive and artificial intelligence research, we critically evaluate two forms of "Justaism" that dismiss LLM cognition by labeling LLMs as "just" simplistic entities without specifying or substantiating the critical capacities these models supposedly lack. Our analysis highlights the need for a more measured discussion of LLM cognition, to better inform future research and the development of artificial intelligence.

1 Introduction

Over 70 years ago, Alan Turing posed a question that has since captivated computer scientists, cognitive scientists, and philosophers alike: "Can machines think?" (Turing, 1950). With the recent proliferation of increasingly capable artificial intelligence systems (e.g., Bubeck et al., 2023)—namely, large language models (LLMs)—variants of this question have made their way far beyond the confines of academic departments.

Although LLMs have been shown to be predictive of human representations and behavior across a broad range of tasks (Binz et al., 2024; Tuckute et al., 2024; Hussain et al., 2024), a number of critics maintain that LLMs cannot be said to possess genuine cognition because they are "just...": "next-token predictors", "function approximators", or "stochastic parrots", and thus lack some essential capacity necessary for "thought", "reasoning", or "understanding" (henceforth, "cognition"). Unfortunately, such deflationary claims often fail to state what exactly this capacity is and have been given the pejorative label "Justaism" (pronounced "just-a-ism") due to the confident self-evidence with which they are wielded (Aaronson, 2023). Such views on the reality of LLM cognition have implications for people's willingness to use them as scientific tools (Binz et al., 2025), and trust such systems in everyday contexts (Mitchell and Krakauer, 2023).

In what follows, we discuss two flavors of Justaism—*anti-simple-objectives* ("it's just a next-token predictor") and *anti-anthropomorphic* ("it's just a machine")—and provide a critical analysis of these positions based on cognitive and artificial intelligence research. We conclude our analysis by putting forth three guiding principles to help clarify the status of LLM cognition.

Although we refer to the flavors' prototypical forms, we also provide specific Justaic examples in a companion webpage (github.com/Zak-Hussain/againstJustaism). The page includes examples found in the literature and public scientific discourse on LLM cognition, as well as (secondary) references and responses to Justaic stances. For instance, it includes anti-simple-objectives claims that LLMs are just "complex", "stochastic", "statistical auto-complete" tools. These kinds of claims are more frequent and often more explicit than their anti-anthropomorphic counterparts, which argue that attributing ostensibly or "profound[ly]" human cognitive capacities to LLMs is not only tempting but also erroneous, and may have "serious [negative] consequences". The former can also reinforce the latter: A Justaic argument might, for instance, claim that because LLMs are clearly "just [next-]token predictors", the best explanation for the mistaken belief that LLMs possess cognition is naive anthropomorphism. Thus, the two forms of Justaism can sometimes appear in concert.

Before proceeding, we clarify the scope of our work. First, our focus is not on whether LLMs exhibit *human* (or human-like) cognition, but on stances opposing the notion of LLM cognition *in general*. We follow a broader conception of cognition that allows for the possibility of ascribing cognition to non-human animals (Andrews and Monsó, 2021) (see also, Section 2.2) and other information process systems (Lyon, 2020). We do, nevertheless, draw on research comparing humans and LLMs, because evidence that LLMs exhibit human-like cognition is, by extension, also evidence that LLMs exhibit cognition in general. Second, we do not base our argument on any specific definition of cognition, nor do we develop one. Instead, we critique Justaic stances against LLM cognition on other grounds, such as internal consistency (Section 2.1) or risk of bias (Section 2.2). Third, although we focus on two forms of Justaism, other substantial perspectives critical of LLM cognition exist and deserve consideration. These views differ fundamentally from Justaism and hence are not the target of our critique. For instance, some empirical research highlights specific LLM cognitive deficits (e.g., Berglund et al., 2024; McCoy et al., 2024; Turpin et al., 2024). Rather than denying LLM cognition outright, such work is better understood as qualifying the extent of cognitive abilities in LLMs. Other research presents substantive theoretical arguments against LLM cognition, for example, by distinguishing *form* (syntax) from *meaning* (semantics) (e.g., Searle, 1980; Bender and Koller, 2020). We view these efforts as making important definitional and conceptual progress on cognition, and they are thus not the target of our critique. We hope that our work can contribute to a better understanding of the arguments in favor of and against LLM cognition, ultimately shaping how we evaluate and compare artificial and biological intelligence.

2 Flavors of Justaism

2.1 Anti-simple-objectives

"It's just a next-token predictor."

Perhaps the most common form of Justaism, which we dub *anti-simple-objectives Justaism*, takes issue with how LLMs are pre-trained (see our companion webpage, github.com/Zak-Hussain/againstJustaism, for examples). The assertion is that because the LLM pre-training objective is simply to predict the masked or next token, LLMs cannot be doing something as complex or substantial as cognition.

Assuming proponents of this view believe that humans possess cognition, anti-simple-objectives Justaism can be questioned by making the following facetious analogy to humans and other creatures shaped by evolution: We humans are "*just* next-child producers", stumbling forward in pursuit of the all-encompassing base objective of inclusive fitness maximization. The point here is not to argue that humans should actually be thought of in such a way but to highlight a common error with this kind of deflationary thinking—the error of assuming that simple base objectives necessarily produce simple systems.

Of course, there are important differences between next-token prediction and inclusive fitness maximization. For instance, the ancestral environment from which we evolved was potentially richer than the online text corpora used to train LLMs. Combined with a sufficiently complex nervous system and other distinguishing factors (e.g., resource competition), biological evolution may lead to the development of *instrumental objectives* that are more conducive to cognition than next-token prediction.

However, even if it were the case that these distinguishing factors were pivotal to the development of instrumental objectives *in humans*, it is nevertheless plausible that cognition-enabling instrumental objectives could be acquired via other means during next-token-prediction-based pre-training. In fact, empirical evidence suggests that LLMs are already employing such instrumental strategies in order to achieve high performance on the base objective (through a process known as *mesa-optimization*, Von Oswald et al., 2023). There is also reason to expect that these instrumental objectives are similar to those of humans (and thus potentially cognition-enabling). After all, the LLM pre-training distribution was generated (mainly) by humans, who would have had various (instrumental) motives driving their text production. An LLM that learns to model these human objectives and incorporate them into its prediction could thus improve its performance on the training distribution by better capturing the data generating process (Hubinger et al., 2019). There is also empirical precedence for this sort of convergence, with research in representational alignment demonstrating that predicting human-generated text can lead to increased alignment between LLMs and human brains (Sucholutsky et al., 2023; Binz et al., 2024).

Relatedly, LLM (instrumental) objectives need not be especially complex to be on par with those of human beings. After all, many foundational theories of human cognition posit relatively simple objectives as fundamental components, with prominent examples including predictive brain theories (e.g., *Bayesian brain*, *predictive coding*, *active inference*, Clark, 2013). Notably, these objectives may not be so different from next-token prediction, which raises a similar question to the evolutionary analogy that opened this section: If simple predictive objectives are generally considered insufficient for the development of cognition, might it be that humans similarly lack genuine cognition?

Finally, it is important to qualify that most contemporary LLMs not only are (pre-)trained with next-token prediction but also go through several stages of fine-tuning. These often include reinforcement-learning from (subjective) human feedback (Bai et al., 2022) and (objective) rule-based rewards (Guo et al., 2025), which are targeted at improving the model's helpfulness. As such, it is now often factually incorrect to claim that LLMs are only trained to predict the next token, although it is still true that the vast majority of data and compute goes into such pre-training (see, e.g., Guo et al., 2025).

Ultimately, the extent to which next-token prediction enables or precludes cognition is a question that requires further theoretical and empirical research. Nevertheless, we hope that the above arguments demonstrate that it is *by no means self-evident* that an LLM is devoid of cognition.

2.2 Anti-anthropomorphism

> *"It's just a machine."*

A second common form of Justaism, which we dub *anti-anthropomorphic Justaism*, claims that attributing cognition to machines constitutes a fundamental error. This form of Justaism is less prominent than *anti-simple-objectives Justaism* (with fewer examples on our companion webpage, github.com/Zak-Hussain/againstJustaism), but arguably equally problematic. In its strongest form, it argues that such thinking commits a category error because cognition is *by definition* a human capacity. On this view, the essential capacity that LLMs lack and humans possess is just that: humanness.

Although logically valid, we would argue that this view is unproductively restrictive. Advances in scientific theory often come from generalizing concepts beyond their initial application. One instructive example comes from animal cognition research, where, in response to a growing body of empirical evidence, researchers began to see great utility in ascribing capacities previously thought to be uniquely human, including emotion, self-awareness, or consciousness, to non-human animals (De Waal, 2016). We believe it should be *in principle* acceptable to make such conceptual generalizations for information processing systems more broadly.

There are, of course, more moderate forms of anti-anthropomorphic Justaism. For instance, one might take the view that although it is not a problem *in principle* to talk about LLM cognition, the burden of evidence for doing so should be set very high. One reason for this would be to guard against the Eliza effect (Mitchell and Krakauer, 2023), which refers to the human propensity to all-too-liberally ascribe "thought" to even the simplest of machines (Weizenbaum, 1976).

Although we agree that it is important to reject naive anthropomorphism, we note that running counter to anthropomorphism is another, perhaps more infamous, human tendency: anthropocentrism. Regarding cognition, anthropocentrism is the tendency to view capacities such as "thought" as so unique that it would not make sense to ascribe them to "lesser" systems, such as non-human animals (see, e.g., Singer, 2011; Harris and Anthis, 2021). In the context of artificial intelligence, it can be observed in the well-documented phenomenon of algorithmic aversion—the human tendency to rely more on human advisors over equally good or better-performing algorithms (Jussupow et al., 2022). Anthropocentrism may ultimately have implications for the adoption of novel technologies that have the potential to contribute to human wealth and well-being.

In light of humans' countervailing tendency to view their own cognition as exceptional, we would advocate for specifying more precisely the forms of cognition in question and the evaluative criteria to be employed. We believe this will enable more substantive discussions of and comparisons between the capabilities of humans and other information processing systems.

3 Conclusion: Toward a more measured discussion

In support of a more measured discussion of LLM cognition, we would like to advance three guiding principles: (i) modesty regarding human cognition (and our understanding of it), (ii) consistency for future work comparing humans and LLMs, and (iii) a focus on empirical benchmarks.

Regarding modesty, we would reiterate that human history is littered with delusions of human exceptionalism (De Waal, 2016). This is despite our limited understanding of the mechanisms underlying cognition. Thus, although we fully support cautioning against the dangers of (naive) anthropomorphism, we see the need for a backstop against the opposite tendency: viewing human cognition as too special to also be ascribed to LLMs.

Regarding consistency, we would reiterate the need for consistent goalposts: Are we applying the same standards to LLMs as we would to humans? For instance, if we wish to reduce LLM cognition to its pre-training objective (i.e., next-token prediction), we must show why the same reductionism should not apply to humans as well. Similarly, when LLMs commit errors that appear so elementary to us as to discredit LLM cognition, it is important to recall the host of fallacies and illusions to which humans are susceptible and which, consequently, we may not so easily identify or view as significant. These considerations not only help guard against certain biases (e.g., algorithmic aversion), but they can also provide a new perspective on human cognition by helping identify aspects of cognition that are, in fact, uniquely human. For instance, it has been argued that (current) LLMs probably lack sentience, consciousness, or self-awareness (Chalmers, 2023)—capacities that are thus unique to humans and other animals.

Finally, we are sympathetic to (Turing, 1950)'s view (among others, e.g., Niv, 2021) that discussions of cognition should focus on observables. As Trott et al. (2023) note, axiomatic rejections of LLM cognition can lead to positions that have no empirically testable implications. Not only does this run contrary to good scientific practice, but it can also lead to investigations of LLM cognition that lack practical relevance. After all, it is predominantly the behavior of a system that impacts the world. Consequently, we believe in the need for clear and consistent empirical benchmarks (e.g., Chollet, 2019) that allow for direct evaluations of the cognitive capacities of humans and LLMs.

Ultimately, the jury is still out on the existence and extent of LLM cognition. We hope that these principles can help researchers move beyond Justaic reasoning towards a deeper, more measured understanding of the cognitive capacities of LLMs.

4 Limitations

Our work has two important limitations. First, we detail only two major forms of Justaism, but there are other stances in the literature that may also qualify as Justaic. For instance, a third could be characterized as *anti-memorization Justaism*, which asserts that LLMs are not doing cognition because they are simply reproducing patterns learned during training. Unfortunately, these objections often fail to: (i) provide evidence of the extent to which the model is, in fact, relying on memory, (ii) justify why such memorization is so at odds with cognition, and (iii) acknowledge that humans often rely on memorization for tasks that are ostensibly reasoning-based (e.g., Bors and Vigneau, 2003; Jaeggi et al., 2008).

Second, because our main focus is to argue against unsubstantiated claims and call for a more measured discussion on LLM cognition, we do not make a substantive positive argument for or against LLM cognition in this work. Doing so would involve considering and adjudicating between different definitions and operationalizations of cognition and related constructs (e.g., intelligence; Legg and Hutter, 2007). Fortunately, efforts to this effect are already underway (e.g., Chollet, 2019). While the task of defining cognition is undoubtedly complex—spanning disciplines, methodologies, and philosophical traditions—we maintain that this complexity does not undermine our central thesis: LLMs should not be dismissed as lacking cognition merely because they are trained via next-token prediction or because they are machines. We hope future work will continue to clarify and refine the concept of cognition in ways that help avoid unwarranted deflationary stances toward artificial intelligence.

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