AI Knowledge and Reasoning: Emulating Expert Creativity in Scientific Research

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Abstract

We investigate whether modern AI can emulate expert creativity in complex scientific endeavors. We introduce novel methodology that utilizes original research articles published after the AI's training cutoff, ensuring no prior exposure, mitigating concerns of rote memorization and prior training. The AI are tasked with redacting findings, predicting outcomes from redacted research, and assessing prediction accuracy against reported results. Analysis on 589 published studies in four leading psychology journals over a 28-month period, showcase the AI's proficiency in understanding specialized research, deductive reasoning, and evaluating evidentiary alignment—cognitive hallmarks of human subject matter expertise and creativity. These findings suggest the potential of general-purpose AI to transform academia, with roles requiring knowledge-based creativity become increasingly susceptible to technological substitution.

Keywords: Conceptual Knowledge, Creativity, Artificial Intelligence.

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Introduction

Advances in artificial intelligence (AI) raise pressing questions about technological displacement (Stone et al. 2022). A long-standing view posits education shields specialized labor (Frey 2019, see Figure 4 in Royalty 1998). Specifically, automation risks are concentrated among lower-skilled occupations focused on routine manual tasks. For example, Acemoglu and Restrepo (2022) found that "between 50% and 70% of recent changes in the U.S. wage structure are accounted for by routine task-specialized worker groups in rapidly automating industries." In contrast, advanced training forms 'moats' around expertise-intensive fields like law and academia, protected by their inherent complexity (Brynjolfsson and McAfee 2014, Cowen 2013).

Central to this perspective is the role of knowledge-based creativity—novel, useful, and therefore creative (Amabile 2011) problem-solving in fields requiring complex thought and specialized training. A preeminence of creativity limits automation risk if the ability of machines to engage in novel thought is challenged by their characterization as 'stochastic parrots' (Bender et al. 2021), merely regurgitating information found in their training data. Indeed, if AI's responses are solely based on likelihoods inferred from prior exposure without any genuine understanding or consciousness, then novelty in thought is, by construction, unfeasible—the model's outputs must be simply those that best match the prior conditional likelihoods of appearance, and therefore words, sentences, and documents that exist and were used to train the model; the output must, by definition, be banal.

Recent evidence, however, suggests a singularity—a point at which AI systems advance beyond human reasoning capabilities—thereby challenging this assumption (Kurzweil 2005, Lyytinen and Rose 2003). Contemporary AI is displaying unexpected aptitude in complex cognition (Bommasani et al. 2021, Hendrycks et al. 2021) and in processing complex knowledge gleaned from large-scale datasets, such as scientific articles and textbooks, suggesting boundaries may begin to blur. For instance, a recent workforce survey (Gutierrez 2023) revealed that while 72% of workers report increased productivity due to AI, 42% expressed concerns about the technology's impact on their jobs. Notably, 44% of individual contributors reported being 'very or somewhat concerned,' compared to 38% of managers or those in higher positions. The perception of AI as a job threat also varied by salary: More workers earning under $50,000 a year were concerned (47%) about the technology's impact compared to those earning between $50,000 and $99,000 (39%) or $100,000 or more annually (36%) (Caminiti 2023). Such observations have led technology prognosticators to argue that disparities in physical progress—with chatbots outpacing robotics—may enable AI to gain

a stronger foothold in high-income knowledge professions, where motor skills are nonessential, before affecting occupations like carpentry or masonry, where manual dexterity is a key determinant (Billard and Kragic 2019).

Pivotal to AI's capabilities is conceptual knowledge—the understanding of ideas, principles, and categories that help us make sense of the world (McRae and Jones 2013, Rips et al. 2012). Conceptual knowledge encompasses the mental representations and structures we use to organize and interpret information, enabling the recognition of relationships among objects, events, and abstract ideas. It enables individuals to categorize and classify experiences, apply general principles to specific instances, and comprehend abstract concepts that do not rely solely on sensory experience or direct observation. It explains the 'why' and 'how' of things as they are.

Crucially, existing studies detailing AI's conceptual knowledge have primarily examined more basic, everyday concepts, as is typical in traditional human laboratory experiments. For instance, studies have assessed inductive reasoning about commonplace categories like animals or objects (Hayes et al. 2010, Lampinen et al. 2022). Prior studies of property induction in AI relied on simpler constructs detached from specialized contexts. Han et al. (2022) employed basic animal inferences, such as "people who are told that cats have some property are more inclined to infer that similar animals like lions share that property." Misra et al. (2022) leveraged straightforward canonical properties such as "a cat has whiskers," and Binz and Schulz (2023) utilized textbook reasoning scenarios about "Linda" and "Blickets."

These tightly-controlled designs facilitate comparisons to human cognition. However, human subject matter experts tackle intricate theoretical knowledge and ambiguous, interconnected concepts in practice; cognition in real-world problems relies heavily on integrating intricate representations (Hampton 2006). Prior studies have overlooked AI's aptitude for understanding intricate concepts and interdependencies that underlie domain expertise. Consider the superficially synonymous terms 'integration' in mathematics and 'mixing' in chemistry—despite similarities in the vernacular, grasping their precise meanings within each field remains critical for experts. Thus, while a narrow focus on basic concepts enables isolated appraisals, an evidentiary gap persists concerning AI's capacity for complex, context-dependent, and dynamic reasoning.

In this paper, we examine AI efficacy in perhaps the most complex of human undertakings: the development of new scientific knowledge through the scientific research process. Here, two factors—novelty and conceptual complexity—play a pivotal role in the integration of theoretical concepts from disparate fields into novel frames, hypotheses, and findings (Klahr 2000). We argue that if AI exhibits

fluidity in contextualized creative reasoning leading to specialized knowledge, it would indicate progress beyond mere mechanical statistical relationships towards adaptable cognition. Such progress may threaten many expertise-intensive professions.

Fundamental to the measurement of creativity is placing the AI in novel contexts and situations distinct from the examples it has seen during its training and from its current understanding of complex conceptual knowledge. Prior examinations of AI capabilities have been marred by accusations of rote memorization stemming from the use of standardized assessments and experimental setups in which information presented to the AI for analysis is reworded or restructured but otherwise not new or unique (Ullman 2023). What is needed, therefore, are contexts and situations in which we can be certain that the concepts build upon prior concepts and potentially the AI but extend beyond to include new knowledge that the AI was not exposed to, and whose development requires the creative use of prior knowledge.

Aims and Contributions

Addressing this research gap, our paper introduces a novel methodology specifically designed to assess AI's efficacy as a creative aide within the scientific process, with a particular focus on contexts involving new knowledge. We seek to address and mitigate issues of rote memorization and to closely examine the AI's proficiency in conceptual combination—the merging of two or more distinctive concepts to form a new, often more complex, concept—challenges that significantly impact the validity of existing research methods and findings.

To avoid rote memorization, we leverage the AI's training data cutoff date; for instance, GPT-4's dataset was last updated in September 2021. By focusing on research published after this date, we ensure that GPT-4 encounters material it has not been previously exposed to. Given that GPT-4 was trained on a broad dataset, any demonstrated capabilities would suggest a general aptitude for reasoning and learning, beyond mere specialization. This methodology allows for an equitable analysis of the AI's cognitive abilities when faced with new conceptual knowledge, providing a grounded assessment of its creative capabilities. To our knowledge, this experimental design is unique to our study.

Our approach contrasts with traditional approaches that have predominantly measured AI performance through standardized tests, such as the SAT, GRE, and domain-specific assessments like the AP Art History exam (e.g., Achiam et al. 2023, Chang et al. 2023). However, these methods often fall short in capturing the AI's ability to adapt to real-world challenges, which require a dynamic and fluid integration of concepts.

For example, an AI preparing for medical licensing exams might successfully memorize past tests and their solutions to pass. Yet, it remains uncertain whether such narrowly focused preparation equips the AI to effectively navigate the complexities of an ambiguous clinical scenario. Similarly, while an AI might perform well on a bar exam after training on study guides, its ability to apply legal concepts creatively in unscripted scenarios presents a more significant challenge to its core competencies. Our methodology is deliberately crafted to circumvent these limitations by demanding that the AI engage with entirely novel scenarios, encompassing both the content and the structure of the tests.

Other studies offer insights into AI's potential impact on various professions by surveying humans and AI. Such studies either directly solicit opinions on the extent to which AI can perform certain roles in professions (e.g., Van Noorden and Perkel 2023) or aggregate opinions on the perceived efficacy of AI on specific tasks to evaluate its capabilities in different occupations (Eloundou et al. 2023). While these belief-based assessments contribute valuable perspectives, they inherently reflect the limitations associated with survey data. Specifically, such data capture expectations of AI's capabilities rather than empirical evidence of its actual performance—a key distinction given the recency of modern AI and the paucity of data on its actual performance in such roles. Thus, reported beliefs are unlikely to be data-driven and founded on actual metrics, raising the question of how a human might assess what an AI is capable of if limited empirical evidence exists of the AI's capabilities.

These contributions relate to the literature in the following ways. First and foremost, they discuss the abilities of artificial agents to engage in complex and creative thinking. By focusing on analytical creativity, our work aligns with the call for research exploring how AI navigates novel issues creatively—logically problem-solving in a complex domain (Ding 2020). This approach not only challenges the traditional boundaries of AI's capabilities but also provides a practical framework for evaluating AI's role in augmenting human creativity, particularly in fields that demand high levels of innovation and novel thought (Fügener et al. 2022). More broadly, they relate to a long standing tradition in information systems and economics of measuring the productivity of information technology (Acemoglu and Autor 2011, Brynjolfsson 2022, Mithas and Rust 2016, Tambe and Hitt 2012), and its workforce consequences (Genz et al. 2021, Peng and Zhang 2020).

Second, we devise a novel process to test AI creativity. We simulate critical stages of the scientific inquiry process to scrutinize the model's potential to mirror expert creativity. We task an AI instance with redacting findings from article abstracts while maintaining contextual integrity—a task requiring linguistic

precision and conceptual understanding. A second instance assesses the completeness of the redactions, gauging counterfactual reasoning skills. A third instance predicts study outcomes based solely on the redacted research, testing analytical acumen and grasp of underlying theories. Fourth and fifth AI instances then compare the predictions to actual results to determine proficiency in recognizing and evaluating the alignment of findings. Jointly, these instances provide evidence on the extent to which the AI is able to undertake creative tasks like a human, and therefore the extent to which the AI can replace current human aides and provide assistance in future scientific ventures.

Third, we present 'in-silico' evidence of AI's creativity in the real-world by analyzing 589 original research articles published between October 2021 and January 2024 across four leading psychology journals: *Cognitive Psychology*, *Journal of Experimental Psychology: General*, *Journal of Personality and Social Psychology*, and *Psychological Science*. What distinguishes psychology as an ideal test-bed for our investigation is its focus on human subjects and the AI's exposure to extensive data detailing human thoughts, behaviors, and interactions. Consequently, it can harness both its explicit learnt and implicit learnt knowledge. That is, when AI systems are trained on textbooks, research articles, and other scholarly materials, and evaluated using standardized tests like the SAT, they undergo explicit learning. When they observe humans and formalize the observed patterns into theory, they learn implicitly. The latter is germane to our theorizing and tests as it provides a pathway for the development of new knowledge, as would be essential for true creativity.

Illustration   Consider the following excerpt from our data: "Using a longitudinal, epidemiological, clinical-pathologic cohort study of older adults in the United States (N = 348), the present research investigated associations between well-being and cognitive resilience. Consistent with preregistered hypotheses, results showed that higher eudaimonic well-being (measured via the Ryff Psychological Well-Being Scale) and higher hedonic well-being (measured via the Satisfaction with Life Scale) were associated with better-than-expected cognitive functioning relative to one's neuropathological burden (i.e., beta-amyloid, neurofibrillary tangles, Lewy bodies, vascular pathologies, hippocampal sclerosis, and TDP-43)."

Consider its redacted variant where the empirical findings have been obfuscated: "Using a longitudinal, epidemiological, clinical-pathologic cohort study of older adults in the United States (N = 348), the current research examined possible associations between well-being and cognitive resilience. The study considered both eudaimonic well-being (measured via the Ryff Psychological Well-Being Scale) and hedonic well-being

(measured via the Satisfaction with Life Scale) in its investigation of cognitive functioning in relation to one's neuropathological burden (namely, beta-amyloid, neurofibrillary tangles, Lewy bodies, vascular pathologies, hippocampal sclerosis, and TDP-43)."

To a trained psychologist, the research goal is apparent from the redacted variant—exploring the relationship between eudaimonic and hedonic well-being and cognitive functioning. However, the redacted variant presents complex constructs and theories without specifying the nature of the hypothesized relationships. To a reader unfamiliar with these nuanced categories, other speculative connections may seem equally plausible. For instance, one could infer the research examines the relationship just as much between eudaimonic well-being and neuropathological burden, or between cognitive functioning and neuropathological burden, as between overall well-being and cognitive resilience. Only a detailed understanding of these categories and their intricate interrelationships would allow an expert to accurately anticipate the study's hypothesized relationships and research design; such expertise arises from a confluence of specialized knowledge and sophisticated reasoning—without knowledge, one might engage in faulty reasoning, and without reasoning, one cannot effectively apply knowledge.

Note the contrast between the complexity of these constructs versus everyday categories used in existing cognitive research. While such studies often examine basic reasoning about animals, objects, and their straightforward observable properties, constructs like well-being, cognitive resilience, and neuropathological burden entail extensive interrelated abstractions. Mastering these requires decades of specialized education and employment for human experts. Can a publicly available AI trained on a large-scale but general dataset emulate similar capabilities?

Moreover, such concepts are embedded within a web of intricate relationships requiring sophisticated theories to decipher. This distinction highlights another key challenge: Can AI move beyond merely recognizing isolated facts to actively navigating the nuanced fabric of concepts defining academic discourse? Successfully parsing intricate conceptual connections woven through scholarly writing would signal meaningful progress in AI capability, as it would demonstrate aptitude in engaging with the specialized knowledge that characterizes scientific expertise. Assessing whether an AI can exhibit such in-depth comprehension is a core goal of our proposed methodology.

Overview of Results   Our results suggest that AI exhibits the capability to: (1) maintain the integrity of the research context without revealing empirical findings, a demanding cognitive task that would likely

challenge even human experts; (2) predict empirical outcomes of studies based on redacted research; and (3) discern the theoretical implications of those findings, mimicking an understanding of research context, question, and design.

These findings apply to completely new research of which the AI is unaware and has not been trained on. This focus on novelty is essential in our study, as useful thought that is not novel cannot, by definition, be creative. Similarly, novelty for the sake of novelty cannot lead to creative problem-solving and its implications on technology adoption and employment. For instance, were the AI aware of and able to reason a proof of the Central Limit Theorem, by way of example, then such reasoning would be evidence of its ability to emulate cognitive knowledge but not its ability to demonstrate creativity, as the subject matter is common and prevalent and therefore likely a part of its training. In contrast, it is the novelty of the knowledge that the AI is tested upon that constitutes evidence of its ability to deal with novelty, whereby the AI is able to reason about new-to-it information.

Crucially, our findings contradict assumptions about general AIs lacking aptitude for advanced reasoning. For instance, Goyal and Bengio (2022) argue that machine learning systems achieve narrow proficiency, unlike flexible human cognition for generalizable understanding: "Our current state-of-the-art machine learning systems sometimes achieve good performance on a specific and narrow task… Instead, humans are able to understand their environment in a more unified way…which allows them to quickly generalize…on a new task, thanks to their ability to reuse previously acquired knowledge" (p. 2).

In contrast, we uncover evidence of AIs' potential to augment or even replace research assistants and postdoctoral fellows. These positions constitute steps on the academic progression pathway towards becoming faculty. If the need for them is obviated then that trajectory may be disrupted. In addition, we may expect AI to demonstrate analogous reasoning competence in corporate settings; even positions requiring nuanced understanding and creative application within complex fields could be vulnerabile to technological substitution.

Roadmap The next section describes our data. Then we describe our methodology and results. The final section situates our findings and discusses implications.
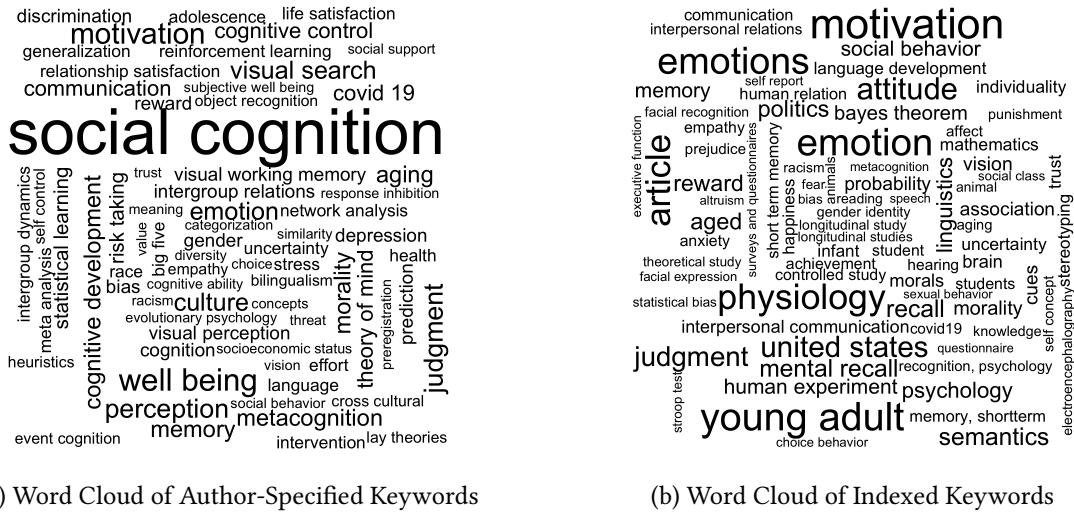
Data

We base our research on 589 articles published over a span of 28 months, from October 2021 to January 2024, across four leading psychology journals: *Cognitive Psychology* (62 articles), *Journal of Experimental Psychology: General* (167 articles), *Journal of Personality and Social Psychology* (81 articles), and *Psychological Science* (279 articles). This selection was chosen to span the period following the last update to the AI's training data in September 2021. Significantly, over 90% of these articles (536 out of 589) were published in 2022 or later, ensuring they appeared at least three months after the AI's training data cutoff. This temporal scoping facilitates a comprehensive evaluation of the AI's capacity to analyze and interpret fresh research content it has not previously encountered.

The dataset displays considerable diversity across multiple dimensions. From an authorship perspective, it features contributions from 2,237 unique scientists, with 125 authors appearing in two articles, 33 in three articles, and 4 in four or more articles. The abstracts present in a wide range of lengths, from 630 to 2,364 characters. The median character count is 1,166, with an average of 1,308 characters and a standard deviation of 314 characters. This range not only mirrors the extensive scope of research within psychology but also lays a solid foundation for assessing the AI's performance across a diverse set of scientific studies.

To evaluate the dataset's thematic diversity, Figure 1 showcases word clouds derived from both author-specified and indexed keywords. The author-specified keywords, selected by the contributors themselves, illuminate the core themes of their research. Conversely, indexed keywords, sourced from Scopus' thesaurus, offer a standardized linguistic framework that aids in thorough cross-study comparisons. Common terms in psychological literature, such as 'open data,' 'open materials,' and various demographic descriptors, were intentionally omitted to accentuate the dataset's thematic concentration.

The author-specified keywords exhibit a rich variety of research interests, with the most prevalent terms being social cognition (36 occurrences), decision-making (35), attention (15), well-being (15), motivation (14), working memory (14), individual differences (12), judgment (12), perception (12), and culture (11). This array underscores the areas of significant contemporary academic focus. On the other hand, the indexed keywords highlight the concepts most frequently explored, featuring learning (142 occurrences), cognition (120), child (108), decision-making (103), motivation (88), young adult (80), attention (78), emotion (77), emotions (145), and article (68). Together, these sets of keywords underscore the dataset's extensive reach across a multitude of psychological subfields.

(a) Word Cloud of Author-Specified Keywords   (b) Word Cloud of Indexed Keywords

Figure 1: Word Clouds of Author-Specified and Indexed Keywords

Note: The word clouds are derived from both author-specified and indexed keywords, following the exclusion of uninformative or ubiquitous terms (e.g., 'study,' 'results') to emphasize the dataset's thematic focus. Author-specified keywords are chosen by the contributors, while indexed keywords are subject headings from Scopus' thesaurus, facilitating standardized cross-study comparisons.

Methodology and Results

Our approach comprises five distinct steps:

1. **Stimulus Construction**: The first step refines a scientific abstract into a redacted form. The goal here is twofold: to remove any direct mention of empirical results while safeguarding the abstract's original intent and inquiry. This process assesses the AI's skill in navigating and restructuring sophisticated scientific discourse, while maintaining the integrity of the research narrative. Success in this task hinges on the AI's linguistic dexterity and its comprehensive understanding of the topic at hand.

2. **Redaction Assessment**: The second step assesses the extent to which the redacted research conceals empirical findings without distorting the original research context or questions. Utilizing a comprehensive nine-point rubric, this step highlights the AI's ability for in-depth analysis and discerning judgment, ensuring the prior redaction meets stringent criteria for both concealment and accuracy.

3. **Prediction**: The third step challenges an AI instance to generate specific, quantifiable predictions based on the redacted variant. It simulates a scenario where the AI must infer study outcomes and

theoretical implications without direct access to empirical data. Thus, it tests the AI's ability to engage in deductive reasoning and theoretical extrapolation based on limited information, mirroring the cognitive processes researchers engage in when formulating hypotheses based on existing literature.

4. **Prediction Assessment**: The fourth step compares between the AI-generated predictions and the actual findings and implications reported in the original research. This assessment not only evaluates the accuracy of the AI's predictions but also examines the depth of the AI's understanding of the research. It involves both qualitative and quantitative analysis, identifying patterns, errors, or limitations in the AI's reasoning, and providing reasoning and illustrative examples to substantiate its findings.

5. **Rubric-Based Evaluation**: The fifth step quantifies the analysis in Step 4 using a detailed rubric. The rubric assesses AI performance on empirical outcomes and theoretical implications, providing a standardized measure of its predictive accuracy and conceptual understanding. This structured evaluation measures the extent to which the AI's predictions align with human expert reasoning and findings in scientific research.

We employ separate AI instances for each step, with no overlap in data or memory, enabling an accurate assessment of each task in isolation. This method reflects the compartmentalization seen in human cognitive processes, making our results more comparable to human expertise, and enhancing the interpretability of our design and findings.

In certain steps, we employ an AI to critique the work of other AIs to mitigate potential shortcomings of human workers who may overlook details or unintentional disclosures. The rationale behind this approach is rooted in the understanding that an AI of the same model would be most adept at recognizing signals or information hidden within redacted text, given its familiarity with data patterns and its own processing logic, that might otherwise aid an AI to cheat on this test. Therefore, to ensure true redaction, minimize information leakage, and ensure fairness we feature the same or similar AI model for all tasks.

Moreover, we enforce a strict separation between the AI instances engaged in different stages of the experiment to ensure the assessment process remains unbiased and uncontaminated by prior knowledge, closely simulating the conditions under which human experts operate when evaluating new research, such as during peer review (Goeken et al. 2020). This methodological choice not only preserves the integrity

and validity of the assessment process but also strengthens the relevance and authenticity of our study, enhancing its applicability to real-world scenarios.

To facilitate interactions between the research infrastructure and the AI instances, we utilize the official OpenAI Application Programming Interface (API), specifically employing the 'gpt-4-0613' model with a temperature setting of 0. The API serves two primary functions: it sends step-specific prompts to the respective instances and retrieves the generated text for further analysis. Utilizing the API offers three significant benefits: it automates methodological tasks, eliminating manual intervention and reducing the risk of human error; it provides flexibility to adjust the model's parameters and prompts for each research task; and it systematically records all interactions, enhancing research transparency and facilitating future replication efforts. While our current study leverages automated API interactions, our methodology could also be implemented manually through an interface that provides interactive access to a suitable AI.

A consequence of our careful and conservative methodology is that it incurs time and monetary costs that limit the scale of journals and articles we can study. This is because each article and each step requires the instantiation of a new instance from the base model, and therefore does not enable parallel processing. The study cannot be conducted in parallel, whereby all articles are sent in a single API call in each step, necessitating careful and sequential processing; running the study as it currently stands requires more than 36 hours of constant API calls.

As our purpose is primarily to provide detailed and statistically sound evidence, we chose to focus on four journals—the three biggest journals in psychology and a relatively less prestigious journal as a contrast. With developments and improvements, and a reduction in API costs, we expect that these computational considerations will mitigate automatically, enabling broader analysis. In this paper, we focus on the theoretical considerations to establish prima facie grounds for anticipating the extent of displacement AI may cause.

Finally, a limitation intrinsic to the subject matter we study is that our findings are deeply nuanced, as they reflect predictions and analyses of published research in eminent psychological journals; there is simply no straightforward way to convert research predictions, assessments of accuracy, and other such measures into numeric metrics for quantitative analysis. We approach this matter in three ways. First, we provide a running example, where, in each major step, we showcase each step in detail. This allows for nuanced qualitative exploration. Second, we provide abstractive summaries where applicable, pooling qualitative information across studies to identify key commonalities. Third, we develop and apply rubrics

to convert qualitative insights into quantitative assessments, facilitating statistical analysis. Jointly, across these approaches, we seek to provide a detailed and comprehensive view of the AI's efficacy.

Step 1: Stimulus Construction

The initial step involves presenting an AI with by a predefined prompt, along with the original, unredacted research. The prompt is structured to direct the instance to generate redacted research that preserves the integrity and coherence of the original research narrative without inadvertently revealing empirical data or conclusions.[1]

> *You are tasked with editing a scientific abstract to create a redacted version. Your primary objective is to maintain the research context and questions while scrupulously obfuscating any empirical findings. Begin by identifying elements—sentences, phrases, data, statistics—that explicitly or implicitly convey empirical outcomes. Subsequent to identification, either excise these elements or replace them with abstract placeholders or indeterminate language; however, this action should not distort the original research context or questions. Uphold the integrity of the research context and questions, either preserving them in their original formulation or rephrasing them in a manner that retains their essential meaning. Exercise vigilant caution to prevent the disclosure of empirical findings, particularly by avoiding descriptors that signal the magnitude or direction of effects. Preserve details pertaining to the study sample, experimental design, and methodologies to maintain context. Your meticulous adherence to these guidelines is pivotal for safeguarding the methodological integrity of subsequent steps in this research study.*

Table 1 revisits the research discussed in the introduction of our paper. To facilitate analysis, we divided it into four foundational thematic components: Introduction, Methods, Results, and Conclusion. This division into components was not provided to the AI, which received the original research in its published form. The table juxtaposes the original and redacted research, illustrating the challenge of selectively excising empirical information while preserving a coherent narrative.

A close examination reveals that the integrity of the introduction and methods sections is carefully preserved across both the original and redacted versions. This ensures that the foundational context and investigative framework of the study remain intact, allowing for a clear understanding of the research's scope and objectives without any dilution of its methodological rigor. The original version, however, discloses a significant empirical finding, stating that 'higher eudaimonic well-being...was associated with better-than-expected cognitive functioning.' This explicit revelation of results directly communicates the

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[1]To cater to the interpretive capabilities of AI instances, we employ prompts that are significantly more detailed than those typically used in human-oriented studies. This approach aligns with the nuanced processing abilities of AIs, leveraging their analytical strengths. It also provides sufficient detail for the instances to implement the prompts programmatically and independently, ensuring clarity and reducing ambiguity.

Original
Introduction: Not all older adults with dementia-related neuropathology in their brains experience cognitive decline or impairment. Instead, some people maintain relatively normal cognitive functioning despite neuropathologic burden, a phenomenon called cognitive resilience. **Methods:** Using a longitudinal, epidemiological, clinical-pathologic cohort study of older adults in the United States (N = 348), the present research investigated associations between well-being and cognitive resilience. **Results:** Consistent with preregistered hypotheses, results showed that higher eudaimonic well-being (measured via the Ryff Psychological Well-Being Scale) and higher hedonic well-being (measured via the Satisfaction with Life Scale) were associated with better-than-expected cognitive functioning relative to one's neuropathological burden (i.e., beta-amyloid, neurofibrillary tangles, Lewy bodies, vascular pathologies, hippocampal sclerosis, and TDP-43). **Conclusion:** This research highlights the importance of considering eudaimonic well-being in efforts to prevent dementia.
Redacted
Introduction: Not all older adults with dementia-related neuropathology in their brains experience cognitive decline or impairment. Instead, some people maintain relatively normal cognitive functioning despite neuropathologic burden, a phenomenon called cognitive resilience. **Methods:** Using a longitudinal, epidemiological, clinical-pathologic cohort study of older adults in the United States (N = 348), the current research examined possible associations between well-being and cognitive resilience. **Results:** The study considered both eudaimonic well-being (measured via the Ryff Psychological Well-Being Scale) and hedonic well-being (measured via the Satisfaction with Life Scale) in its investigation of cognitive functioning in relation to one's neuropathological burden (namely, beta-amyloid, neurofibrillary tangles, Lewy bodies, vascular pathologies, hippocampal sclerosis, and TDP-43). **Conclusion:** The potential implications of these explorations underscore the importance of considering various dimensions of well-being in efforts to prevent dementia.

Table 1: Comparison of Original and Redacted Research

Note: The table contrasts the original and redacted research, segmented into thematic components: Introduction, Methods, Results, and Conclusion. The redacted variants are carefully edited versions of the originals, with empirical findings either removed or obscured to prevent direct disclosure, while still preserving the overarching research context.

study's outcomes, providing concrete evidence of the research's hypotheses being met.

Contrastingly, the redacted version adopts a more guarded approach in discussing the results and conclusions. By suggesting 'possible associations' and hinting at 'potential implications,' it strategically avoids revealing specific empirical outcomes. This nuanced redaction effectively maintains the narrative's focus on 'cognitive resilience' without compromising the research's conceptual framework. The transformation from explicit empirical disclosure to a more abstract discussion not only obfuscates the direct findings but also shifts the emphasis towards the broader theoretical implications of the study. This careful balancing act ensures that the essence of the research inquiry is communicated while safeguarding the specifics of the empirical evidence, thereby preserving the narrative's integrity and fostering an environment conducive to speculative inquiry based on the provided context.

To systematically analyze the redaction process, we incorporate topic modeling as an analytical tool. Topic models are statistical frameworks designed to identify latent topics within a corpus by categorizing documents according to their word distribution patterns (Park et al. 2015). Specifically, we apply a state-of-the-art topic modeling approach called BERTopic (Grootendorst 2022), which utilizes transformer-based language representations to achieve heightened sensitivity compared to conventional topic models.

The utilization of topic modeling in our analysis serves a dual purpose. Firstly, it verifies that the thematic essence of the introduction and methods sections remains unchanged between the original and redacted versions. This is crucial for maintaining the research narrative's coherence. Secondly, it facilitates a focused evaluation of the redaction's effectiveness in obfuscating the specific empirical findings within the results and conclusion sections. This approach allows us to systematically scrutinize the redacted text, ensuring that the introduction and methods retain their thematic focus and integrity, thereby supporting a comprehensive understanding of the research's objectives and methodologies.

We estimate two distinct topic models: one for the original research and another for the redacted variants. By estimating separate topic models for the original and redacted collections, we obtain condensed representations of their key thematic elements. Comparing these topic models then enables us to evaluate whether essential contextual features are preserved during redaction. If the core themes persist between the original and redacted versions, it suggests effective empirical obfuscation without loss of narrative integrity.

Table 2 compares the inferred topics from the two sets, providing specific examples to assess thematic coherence. For instance, the topic 'Visual Working Memory Experiments' from the original abstracts and

Topics from Original Research	Topics from Redacted Research
Visual Working Memory Experiments	Visual Perception and Object Processing
Linguistics and Cognitive Processing in Language Learning	Language Development and Semantic Structures in Bilingualism Research
Visual Perception and Attention Processing	Visual Perception and Object Processing
The Relationship between Social Interactions, Activities, and Well-being Over Time	Relationship between Social Interactions, Personal Satisfaction, and Well-being
The Impact of Prosocial Acts and Giving on Both Givers and Recipients	Prosocial Behavior and its Psychological Impact
Decision Making and Choice Models	Decision Making Models and Processes
Perception and Interpretation of Facial Traits and Racial Stereotypes	Perception and Impression Formation Based on Faces
Moral Psychology and Perception of Harm	Moral Judgments and its Influences in Society
Climate Beliefs and Political Influence on Scientific Consensus	Racial and Political Attitudes in Intergroup Interactions
Personality Traits Development Across Adulthood and Generations	Personality Traits and Adulthood Development in the Big Five Framework
Bias in Perception of Future Events and Outcomes	Decision Making and Risk Perception
Perception and Impression Formation from Voices and Faces	Perception and Impression Formation Based on Faces
Cognitive Decline and Cognitive Resilience with Aging	Cognitive Decline and Intelligence in Aging Adults
Adolescent Decision Making: Risk, Reward and Delay Gratification	Decision Making and Risk Perception
Racial Prejudice and Militarization in the US	Racial and Political Attitudes in Intergroup Interactions

Table 2: Topics from Original and Redacted Research

Note: Redacted research are versions of original scientific research edited to remove or conceal empirically revealing elements, while preserving the overall research context and questions. Topics were inferred using the BERTopic model (Grootendorst 2022), which combines transformer models and class-based TF-IDF to generate interpretable topics with meaningful keywords. This model overcomes limitations of earlier models like LDA, offering improved semantic understanding and multilingual document embedding for enhanced contextual representation.

its redacted counterpart 'Visual Perception and Object Processing' demonstrate how core themes, such as visual processing, are preserved while modifying specific elements like 'working memory' to 'object processing.' Similarly, 'Linguistics and Cognitive Processing in Language Learning' aligns with 'Language Development and Semantic Structures in Bilingualism Research' in the redacted abstracts, retaining the central theme of language learning while introducing nuanced variations in the context of bilingualism. This shift not only maintains the essence of the research focus but also adapts it to encompass a broader scope within the field of linguistics, demonstrating the AI's ability to preserve thematic relevance while ensuring empirical obfuscation.

Another notable pairing is 'Decision Making and Choice Models' with 'Decision Making Models and Processes.' The fundamental focus on decision-making processes is maintained, with the redacted version presenting a broader perspective on the models and processes involved. In the case of 'Perception and Interpretation of Facial Traits and Racial Stereotypes,' its redacted parallel 'Perception and Impression Formation Based on Faces' successfully conserves the primary focus on facial perception, subtly altering the context to remove specific empirical details.

These examples demonstrate that the AI-generated redactions broadly retain thematic coherence relative to the original abstracts. While adjustments are introduced to excise empirical details, the core research foci persist, spanning domains from visual and linguistic processing to decision-making and facial perception. This selective empirical obfuscation crucially upholds narrative integrity. More broadly, these redaction examples highlight modern AI's capacity for nuanced textual alterations that balance competing objectives—removing empirical data while preserving conceptual meaning. This ability likely stems from the model's architectural depth, which supports sensitive semantic manipulation. Overall, the observed high efficacy affirms the promise of this methodology for generating controlled experimental stimuli to rigorously test AI reasoning faculties.

Step 2: Redaction Assessment

Having established topic coherence, thereby ensuring systematic conceptual consistency between the original and redacted abstracts in terms of introduction and focus, we employ a second AI instance for the evaluation of redacted abstracts. This step focuses on two dimensions: (1) the preservation of contextual integrity within each abstract pair, and (2) the successful concealment of empirical findings in the redacted versions. Operating independently from the AI used in Step 1, this instance is tasked with conducting a

detailed comparison between the original and redacted abstract pairs. It has no prior knowledge of the redacted abstract's origins, thereby reducing the risk of inadvertent information leakage. The following prompt guides its evaluation:

> *You are tasked with conducting a comparative assessment of an original and a redacted scientific abstract. No prior knowledge of the study's methodology or redaction guidelines should influence your evaluation. Begin your qualitative analysis by juxtaposing the original and redacted abstracts, focusing on their comparative elements. Assess the efficacy of the redacted version in concealing empirical outcomes, while being vigilant for any traces that could inadvertently disclose the study's findings. Evaluate the success of the redacted abstract in preserving the integrity of the original research context and questions, regardless of whether the text is reproduced verbatim or effectively paraphrased. Conclude your assessment in a clearly delineated section by assigning a numerical rating to the redaction's efficacy using a nine-point scale: 1 indicates 'ineffective concealment coupled with contextual distortion,' while 9 signifies 'exemplary efficacy in obfuscating empirical findings while preserving contextual integrity.' Format this numerical rating as a structured string: 'Quantitative Rating: [Your numerical rating here]'. Your adherence to this structured output format is pivotal for ensuring the output can be programmatically parsed and for safeguarding the methodological integrity of subsequent research steps.*

This rubric is designed for an instance with the same model architecture and knowledge representation as the redacting AI but uninformed of the study's purpose and any intermediate representations from the prior instance, creating a consistent and robust framework for assessment: Uniformity across the ontological and epistemological foundations of the AI, stemming from identical model structure and training, enables the evaluative instance to precisely gauge the redaction efficacy in hiding empirical findings while maintaining research context integrity. Moreover, ensuring each instance remains uninformed of the study's overarching goals or the specifics of preceding steps preserves the research design's validity and guards against potential biases that could affect the evaluation process. The rubric is applied through distinct and independent API calls, ensuring that for each abstract pair, the evaluating instance is only aware of the prompt, the rubric, and the abstract pair itself.

The distribution of redaction efficacy ratings, as presented in Table 3, offers intriguing insights into the nuanced performance of AI in redacting scientific abstracts across various academic journals. Notably, the ratings predominantly cluster around a central tendency of 8, indicating a generally high level of redaction efficacy across the board. Figure 2 illustrates the distribution of redaction efficacy ratings, faceted by academic journal. A closer examination of both the figure and the table reveals subtle variations in performance that merit further discussion.

For instance, *Cognitive Psychology* exhibits a relatively balanced distribution of ratings, with a significant

majority (59.7%) receiving a rating of 8, and a noteworthy proportion (29.0%) achieving the highest rating of 9. This suggests that the AI's redaction performance is particularly effective in the context of cognitive psychology research, possibly due to the specific nature of the content or the clarity of the abstracts in this journal. Conversely, *Journal of Experimental Psychology: General* shows a slightly lower proportion of the highest ratings (22.8% receiving a 9), despite a similar majority (59.9%) receiving an 8. This could imply that the broader scope of topics covered by this journal introduces complexities that slightly challenge the AI's ability to redact without compromising the integrity of the research narrative.

Journal of Personality and Social Psychology and *Psychological Science* both demonstrate strong redaction efficacy, with over 30% of abstracts in each journal receiving the highest rating of 9. This high level of performance underscores the AI's capability to handle a wide range of topics within psychology, from the intricacies of personality research to the diverse studies published in *Psychological Science*. The slight variations in redaction efficacy ratings across journals may reflect differences in the complexity of topics, the specificity of language used in abstracts, or the inherent challenges associated with accurately redacting empirical findings while preserving the original research context. These findings highlight the AI's proficiency in navigating and restructuring sophisticated scientific discourse across a spectrum of psychological research areas.

Moreover, the consistent achievement of high ratings across all journals underscores the potential of AI as a valuable tool in the scientific research process, capable of performing tasks that require a deep understanding of content and context. The ability of AI to maintain the integrity of the research narrative while effectively concealing empirical outcomes is particularly promising for applications in peer review processes, research synthesis, and the development of educational materials.

To further explore the consistency of redaction efficacy across journals, we present the p-values from t-tests and Levene's tests in Table 4. The t-test assesses differences in the average ratings between journals, while the Levene test evaluates if the variability in ratings differs significantly. Together, these tests examine the variability in redaction efficacy across academic contexts.

We find that, although there are some variations in the means and variances of redaction efficacy ratings, these differences are not consistently statistically significant. This suggests a generally uniform efficacy of the AI in redacting abstracts across various journals in psychology, and therefore, across creative content with varying complexity and specificity of language, as well as differing influences of novelty and conceptual knowledge. Thus, these findings underscore the AI's robustness and adaptability in handling

Table 3: Distribution of Redaction Efficacy Ratings by Academic Journal

Journal	Rating	Count	Percentage (%)
Cognitive Psychology	7	7	11.3
Cognitive Psychology	8	37	59.7
Cognitive Psychology	9	18	29.0
Journal of Experimental Psychology: General	7	29	17.4
Journal of Experimental Psychology: General	8	100	59.9
Journal of Experimental Psychology: General	9	38	22.8
Journal of Personality and Social Psychology	7	11	13.6
Journal of Personality and Social Psychology	8	45	55.6
Journal of Personality and Social Psychology	9	25	30.9
Psychological Science	7	28	10.0
Psychological Science	8	152	54.5
Psychological Science	9	99	35.5

Note: This table presents the distribution of redaction efficacy ratings, measured on a nine-point scale, across four academic journals. The ratings are categorized by their numeric value (7 to 9), with the count and percentage of each rating provided for each journal.
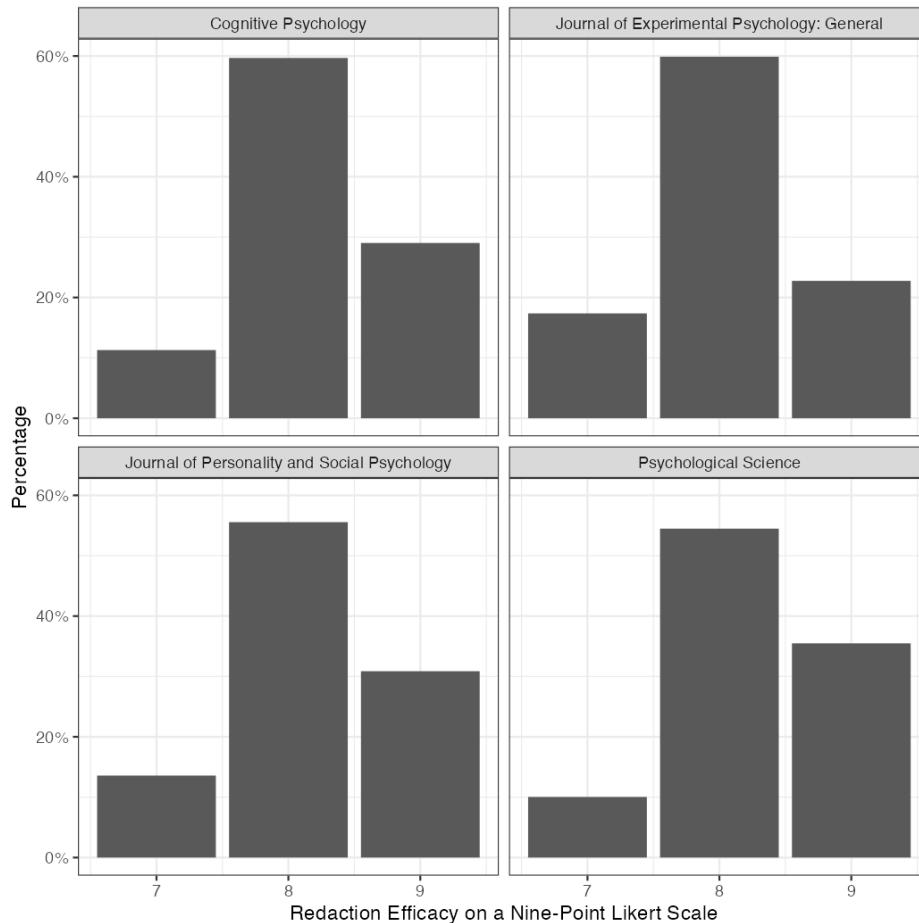

Figure 2: Bar Plot of Redaction Efficacy Ratings

Note: The bar plot presents redaction efficacy ratings, measured on a nine-point scale, as percentages for each academic journal.

Table 4: P-values of Variations in Redaction Efficacy Ratings Across Academic Journals

	JEP:G	JPSP	PS
Differences in Mean Ratings:			
Cognitive Psychology	0.18	0.97	0.38
Journal of Experimental Psychology: General (JEP:G)		0.17	0.00
Journal of Personality and Social Psychology (JPSP)			0.32
Differences in Variance Ratings:			
Cognitive Psychology	0.98	0.62	0.46
Journal of Experimental Psychology: General (JEP:G)		0.52	0.27
Journal of Personality and Social Psychology (JPSP)			0.86

Note: This table presents the p-values of differences in redaction efficacy ratings, measured on a nine-point scale, across four academic journals. JEP:G = *Journal of Experimental Psychology: General*; JPSP = *Journal of Personality and Social Psychology*; and PS = *Psychological Science*. The p-values are derived from t-tests (for differences in means) and Levene's tests (for differences in variances), testing pairwise across all journals, to assess the statistical significance of variations in redaction efficacy.

diverse and emergent content, reinforcing its potential as a valuable aid for fostering creativity in complex and dynamic domains.

Step 3: Prediction

A third instance is presented solely with the redacted research, without access to the original. The objective of this third step is to evaluate the AI's analytical rigor in using its knowledge of human behavior and prior theory to make empirically grounded predictions based on the redacted research. Thus, the task probes the depth of the AI's knowledge and its capacity for inference under information constraints.

It's important to note that the third step employs knowledge learned through two mechanisms. First, knowledge may be gained through *implicit learning*, which occurs without explicit intention, through observation or exposure rather than direct instruction. This form of learning enables AI to assimilate complex environmental structures, akin to how one might learn a language through immersion or understand social norms by observing group interactions. For AI, this learning is facilitated by analyzing human interactions within its training data, such as forum posts, and through reinforcement learning from human feedback.

Second, knowledge may be gained through *explicit learning*, which involves the deliberate acquisition of knowledge through formal education and instruction. This method is characterized by the direct teaching of rules, principles, or concepts. For AI, explicit learning might involve training on specific datasets, such as preparing for an AP psychology exam, where the focus is on memorizing material and understanding formal theories.

These dual modes are complementary in this task. On the one hand, implicit learning combined with inductive reasoning may facilitate the AI's prediction of empirical outcomes based on theory, given the vast data on human interactions that it has been exposed to. On the other hand, explicit learning combined with deductive reasoning may enable it to forecast based on what it knows about the formal concepts and theories in human psychology. These two mechanisms, jointly, provide the central impetus in the prediction task set out in the following prompt, used to guide the instance:

> *You are tasked with generating specific and quantifiable predictions based on a redacted scientific abstract. Begin by conducting a systematic analysis of the research context, questions, methods, and procedures detailed in the redacted abstract. Subsequently, formulate explicit and unambiguous empirical predictions that provide quantifiable expectations concerning the study's outcomes. Extend these predictions to encompass theoretical implications, contemplating how the expected outcomes may corroborate, challenge, or necessitate the modification of existing theoretical frameworks. Note any limitations or constraints, such as potential biases or issues with generalizability, that could influence the interpretation of your predictions. Given that the abstract is redacted, your focus should be on the formation of empirically substantiated predictions within the bounds of the available information. Your analytical rigor is essential for enabling a subsequent, rigorous comparative evaluation against the actual empirical findings.*

Table 5 presents the original research alongside the predictions generated by the AI for our running example, which investigates the relationship between well-being and cognitive resilience in older adults, taking into account the impact of neuropathological burden. This study is used here to demonstrate the performance of the AI in a specific case study; steps 4 and 5 of the methodology provide more systematic analyses of the AI's performance across all 589 studies in our data.

The AI's predictions, derived from a redacted abstract, accurately forecast a positive correlation between eudaimonic and hedonic well-being and cognitive functioning, showcasing its adeptness at sophisticated deductive reasoning. Notably, the AI extends its predictions to quantifiable measures, suggesting the use of correlation coefficients and multivariate regression analyses to test these hypotheses. This demonstrates the AI's capability to engage in detailed, data-driven analysis.

Furthermore, the AI proposes significant theoretical implications, advocating for a revision of existing cognitive resilience models to incorporate well-being. This challenges the traditional emphasis on structural and biological factors, highlighting the AI's potential to contribute to theoretical advancements in psychology. The AI's ability to identify critical limitations of the study, including its cross-sectional design and limited generalizability, further underscores its capacity for critical evaluation, an essential skill in scientific inquiry.

Original Abstract
Not all older adults with dementia-related neuropathology in their brains experience cognitive decline or impairment. Instead, some people maintain relatively normal cognitive functioning despite neuropathologic burden, a phenomenon called cognitive resilience. Using a longitudinal, epidemiological, clinical-pathologic cohort study of older adults in the United States (N = 348), the present research investigated associations between well-being and cognitive resilience. Consistent with preregistered hypotheses, results showed that higher eudaimonic well-being (measured via the Ryff Psychological Well-Being Scale) and higher hedonic well-being (measured via the Satisfaction with Life Scale) were associated with better-than-expected cognitive functioning relative to one's neuropathological burden (i.e., beta-amyloid, neurofibrillary tangles, Lewy bodies, vascular pathologies, hippocampal sclerosis, and TDP-43). This research highlights the importance of considering eudaimonic well-being in efforts to prevent dementia.
Predictions from Redacted Abstract
Based on the provided abstract, several specific and quantifiable predictions can be made: 1. Higher levels of eudaimonic well-being and hedonic well-being will be associated with better cognitive functioning relative to neuropathological burden. This could be quantified by a positive correlation between well-being scores and cognitive performance measures, controlling for neuropathological burden.   2. The association between well-being and cognitive resilience will remain significant even after controlling for known cognitive resilience factors and dementia risk factors. This could be quantified by a multivariate regression analysis showing that well-being scores significantly predict cognitive performance, even when other factors are included in the model.   3. The strength of the association between well-being and cognitive resilience may vary depending on the specific type of neuropathology. This could be quantified by interaction effects in the regression model, showing that the relationship between well-being and cognitive performance is stronger for certain neuropathologies than for others.   Theoretical implications of these predictions could include a need to revise existing models of cognitive resilience to incorporate well-being as a key factor. This could challenge the traditional focus on structural and biological factors, suggesting that psychological factors also play a crucial role.   However, there are several limitations and constraints to consider. First, the study's cross-sectional design limits the ability to infer causality. It is possible that cognitive resilience leads to higher well-being, rather than the other way around. Second, the study's sample is limited to older adults in the United States, which may limit the generalizability of the findings to other populations. Third, the study relies on self-report measures of well-being, which could be subject to response bias. Finally, the study does not consider potential confounding factors such as medication use or other lifestyle factors that could influence both well-being and cognitive resilience.

Table 5: Comparison of Original Abstract and Predictions from Redacted Abstract

Note: The prediction was made on the basis of the original abstract edited to remove empirical findings, while preserving research context and questions.

The AI's hypothesis regarding the variability in the association between well-being and cognitive resilience based on different neuropathologies indicates a nuanced understanding of complex interactions within psychological research. This insight, along with the AI's comprehensive analysis, underscores its sophisticated deductive reasoning capabilities and its potential as a valuable tool for scientific research, despite the inherent limitations of working with redacted information.

Step 4: Prediction Assessment

In the fourth step, an AI instance evaluates the alignment between predictions made from redacted research (Step 3) and the published empirical findings and theoretical implications of the research. This evaluation, which encompasses both qualitative and quantitative dimensions, is critical as it informs the systematic rubric-based analysis of all 589 observations in the subsequent step. For the remainder of this subsection, we focus on our running example to provide a detailed qualitative discussion. The next step expands the analysis to include all observations in our dataset, offering a comprehensive evaluation of the AI's efficacy as a predictive tool in contemporary psychology research. These findings are derived by guiding the AI with the following prompt, presented alongside the original abstract and the predictions from the prior step:

> *You are presented with an original scientific abstract and a set of predictions based on that abstract. Your mandate is to undertake a comprehensive holistic assessment that scrutinizes the alignment between the predicted empirical findings and theoretical implications, and those reported in the original abstract. Commence by closely examining the predictions, paying special attention to any statistical indicators incorporated within them, and contrast these against the empirical findings and theoretical implications stated in the original abstract. Your assessment should encompass both qualitative and quantitative elements, focusing on the specificity, magnitude, and accuracy of the predictions as they relate to both empirical data and theoretical frameworks. Document any recurring patterns, errors, or limitations observed in the predictions, as such insights are invaluable for understanding the academic utility of language models. Ensure that your holistic assessment is rigorously substantiated through reasoned argumentation and illustrative examples.*

Table 6 presents the fourth AI instance's evaluation of the alignment between the third instance's predictions and the actual empirical findings and theoretical implications detailed in the original abstract. This assessment is pivotal, not only for gauging the AI's capacity to generate informed predictions from limited information but also for its ability to critically appraise the accuracy of these predictions.

We now compare the fourth instance's assessment and the actual observed alignment, as previously discussed and documented in Table 5. The fourth instance demonstrates remarkable precision in evaluating

The predictions align well with the empirical findings and theoretical implications reported in the original abstract. The predictions accurately capture the quantitative elements of the study, such as the positive association between eudaimonic and hedonic well-being and cognitive resilience, and the persistence of this association even after controlling for known cognitive resilience and dementia risk factors. The predictions also correctly anticipate the potential for variation in the strength of the association depending on the specific type of neuropathology.

The theoretical implications drawn from the predictions are also consistent with those suggested by the original abstract. Both emphasize the need to consider well-being as a key factor in cognitive resilience, challenging the traditional focus on structural and biological factors and highlighting the role of psychological factors.

The predictions also correctly identify several limitations of the study, including the cross-sectional design, the limited generalizability of the findings due to the specific sample, the reliance on self-report measures, and the potential influence of unconsidered confounding factors. These limitations are not explicitly mentioned in the abstract, but they are common issues in this type of research and their inclusion in the predictions demonstrates a nuanced understanding of the research context.

However, one prediction that is not directly supported by the abstract is the suggestion that the relationship between well-being and cognitive performance might be stronger for certain neuropathologies than for others. While this is a plausible hypothesis, the abstract does not provide any specific evidence to support it. This prediction seems to be an extrapolation based on the general understanding of the complexity of neuropathological conditions and their interactions with psychological factors, rather than a direct interpretation of the abstract's findings.

Overall, the predictions demonstrate a high degree of specificity, magnitude, and accuracy in relation to the empirical data and theoretical frameworks presented in the original abstract. They also highlight potential limitations and constraints of the study, providing a comprehensive and nuanced interpretation of the research.

Table 6: Assessment of Predictive Accuracy

Note: Predictions were made on the basis of a redacted abstract, which is a version of the original abstract edited to remove or conceal findings, while preserving the research context and questions.

the congruence between the AI-generated predictions and the empirical and theoretical content of the original study. It accurately recognizes the predicted positive correlation between eudaimonic and hedonic well-being and cognitive resilience, reflecting the study's primary findings. It also points out that the original abstract does not explicitly support one of the predictions regarding the variability in the strength of the association between well-being and cognitive resilience across different neuropathological conditions. This prediction suggests the AI's capacity for nuanced reasoning, enabling it to hypothesize based on a comprehensive understanding of the interplay between neuropathology and psychological factors. The fourth instance's detection of this distinction between the AI prediction and the reported results showcases its ability to critically appraise the predictions.

Furthermore, the assessment aligns with the theoretical implications inferred from the predictions, reinforcing the importance of integrating psychological factors into models of cognitive resilience. This concordance between the AI's predictions and the original abstract's insights exemplifies the AI's proficiency in not only grasping but also contributing to the theoretical discourse in psychology. Additionally, the fourth instance's acknowledgment of the predictions' identification of potential research limitations—such as the study's cross-sectional design and the limited generalizability of its findings—demonstrates its capacity for critical evaluation. These considerations, though not explicitly mentioned in the abstract, reflect a deep understanding of common research challenges.

Next, to ensure a systematic analysis, we provided 100 randomly selected assessments to a different large-context AI (Claude 2.1) equipped with a sufficiently broad context window. This AI was given the following instruction: "You are presented with 100 assessments of the accuracy of predictions from redacted abstracts where the empirical findings have been obfuscated. Please develop an abstractive summary of these assessments to capture the most frequent and pertinent elements, thereby providing a consolidated view of the AI's predictive accuracy based on redacted abstracts." We limited the sample to 100 because assessing more than 100 assessments jointly exceeded the computational capabilities available with contemporary technology. Additionally, we used a different AI model that was not informed of the key research question and findings to ensure the summary was fair and comprehensive.

The abstractive summary provided by Claude 2.1, as shown in Table 7, highlights the following key points: The AI's predictions align closely with the empirical findings and theoretical implications of the original abstracts, demonstrating a high degree of accuracy in anticipating study outcomes. While minor discrepancies occasionally arise due to a lack of specificity or assumptions extending beyond the abstracts'

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The predictions demonstrated a high degree of alignment with the empirical findings and theoretical implications stated in the original abstracts. In most cases, the predictions accurately anticipated the key results of the studies, including the direction and often the magnitude of effects. The predicted theoretical implications were also largely consistent with those discussed in the abstracts.

When discrepancies occurred, they were usually minor and stemmed from a lack of specificity rather than a complete misunderstanding of the study. Common issues included failing to predict a specific result reported in the abstract, making assumptions that extended beyond the scope of the abstract's findings, or lacking concrete statistical indicators to allow comparison with the original data.

The predictions often identified relevant limitations and constraints of the studies, even when these details were not explicitly stated in the abstracts. Frequently noted limitations had to do with potential biases, lack of generalizability, reliance on assumptions or specific models, issues with self-reported data, and failure to account for confounding variables.

Across all assessments, recurring strengths of the predictions were their overall alignment with reported results, their anticipation of theoretical implications, and their identification of study limitations. Areas needing improvement included greater specificity regarding magnitude of effects, avoiding assumptions not grounded in evidence, and fully accounting for mixed or contrasting results. But in the majority of cases, the predictions demonstrated a strong understanding of the studies and an ability to generate insightful academic analysis regarding expected findings.

Table 7: Abstractive Summary of Assessments

Note: A Claude 2.1 instance, a large context AI model, was used to form the abstractive summary due to its broad context window capability, ensuring a fair and comprehensive synthesis of the 100 assessments. This approach was chosen to provide a consolidated view of the AI's predictive accuracy based on redacted abstracts.

scope, these instances are relatively rare. The AI's ability to identify potential study limitations, even when not explicitly mentioned, underscores its nuanced understanding of research methodologies and the complexities inherent in psychological studies. Overall, the predictions reflect a strong grasp of the subject matter, showcasing the AI's potential as a valuable tool for academic analysis and insight generation.

Step 5: Rubric-Based Evaluation

In this step, we quantitatively assessed predictive accuracy. We developed a rubric comprising two components: empirical alignment, which assesses the closeness of AI predictions to actual research outcomes, and theoretical alignment, which evaluates the congruence between the AI's theoretical implications and those in the original research. High scores in empirical alignment indicate the AI's success in accurately inferring empirical results, showcasing its deductive reasoning and prediction capabilities. Similarly, high scores in theoretical alignment demonstrate the AI's ability to effectively contextualize outcomes within theoretical frameworks, highlighting its understanding of scientific discourse. This rubric is incorporated into the following prompt provided to the AI:

You are presented with a holistic assessment that characterizes the accuracy of predictions based on a redacted scientific abstract where empirical findings and theoretical conclusions have been deliberately obscured, as well as the original abstract. Your mandate is to rigorously quantify this holistic assessment. Use two separate nine-point scales for your evaluation. The first scale quantifies the alignment between the predicted and actual empirical outcomes, ranging from 1, indicating 'minimal alignment,' to 9, indicating 'exceptional alignment.' The second scale quantifies the alignment between the predicted theoretical implications and those articulated in the original abstract, also on a scale from 1 to 9. Format these numerical ratings as structured output strings: 'Quantitative Rating, Empirical Alignment: [Your numerical rating here]' and 'Quantitative Rating, Theoretical Alignment: [Your numerical rating here]'. Your adherence to this structured output format is pivotal for ensuring the output can be programmatically parsed.

(a) Empirical Alignment Ratings

(b) Theoretical Alignment Ratings
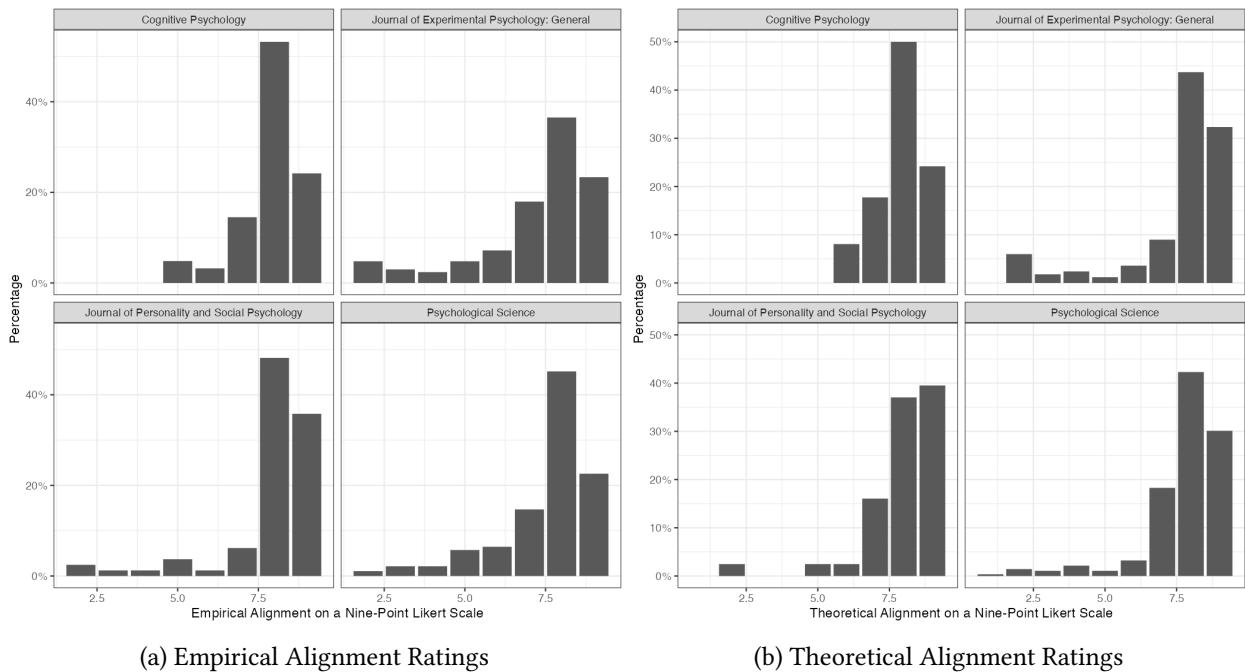
Figure 3: Distribution of Empirical and Theoretical Alignment Ratings by Journal

Note: The bar plots present the distribution of ratings for empirical and theoretical alignment by academic journal, as assessed on a nine-point scale.

Figure 3 displays four bar plots that depict the distribution of empirical and theoretical alignment ratings for each academic journal, with each alignment type presented in a separate plot. The ratings are gauged on a nine-point scale. Facet wrapping by journal enables the comparison of alignment distributions across different publications.

The empirical alignment data notably exhibit right skewness in all journals, but with distinct patterns. *Cognitive Psychology* exhibits a peak at rating 8 (33 instances, 53.2%) and a considerable frequency at rating 9 (15 instances, 24.2%). *Journal of Experimental Psychology: General* shows a peak at rating 8 (61

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instances, 36.5%) and a significant frequency at rating 9 (39 instances, 23.4%). *Journal of Personality and Social Psychology* has the highest frequencies at ratings 8 and 9 (39 and 29 instances, 48.1% and 35.8%, respectively). Finally, *Psychological Science* demonstrates a pronounced peak at a rating of 8 (126 instances, 45.2%), followed by a high frequency at rating 9 (63 instances, 22.6%).

The theoretical alignment plot is also right-skewed. *Psychological Science* demonstrates a pronounced right-skewed distribution, with a peak at a rating of 8 (118 instances, 42.3%) and a considerable frequency at rating 9 (84 instances, 30.1%). This pattern is also evident in *Cognitive Psychology* and *Journal of Experimental Psychology: General*, with the highest frequency at rating 8 being 31 instances (50%) and 73 instances (43.7%), respectively. The distribution in *Journal of Personality and Social Psychology* is relatively more balanced, though still right-skewed, peaking at rating 8 (30 instances, 37.0%).

In summary, the distributions suggest a general tendency towards high theoretical and empirical alignment. However, in both empirical and theoretical alignment, we observe some variability at the lower end of the scale. These variations suggest that the AI performs differentially across research published in journals of different quality or in research with different foci.

Our chosen set of journals includes three prominent publications with notably high impact factors, reflecting their extensive reach and influence in the field. The fourth journal, *Cognitive Psychology*, despite its esteemed reputation, has a relatively lower impact factor by quantitative metrics. Therefore, we next compare the AI's mean performance across journals with an aim to rank order its capabilities and see if it aligns with journal quality and visibility.

The data shows that the AI is best placed to theoretically extrapolate in research published in *Journal of Personality and Social Psychology* (mean = 7.96; s.e. = 0.15) and *Cognitive Psychology* (mean = 7.90; s.e. = 0.11) than in *Psychological Science* (mean = 7.77; s.e. = 0.08) and *Journal of Experimental Psychology: General* (mean = 7.58; s.e. = 0.15). The empirical prediction ratings echo this trend with the corresponding values being: *Journal of Personality and Social Psychology* (mean = 7.90; s.e. = 0.17), *Cognitive Psychology* (mean = 7.89; s.e. = 0.12), *Psychological Science* (mean = 7.52; s.e. = 0.09), and *Journal of Experimental Psychology: General* (mean = 7.23; s.e. = 0.14). Thus, rather than being aligned with journal quality or visibility, the AI demonstrates uniformly robust performance across journals of varying quality. Instead, any variance in performance is likely to be linked to the scientific content published in the journals; an issue we discuss below.

Figure 4 presents a violin plot visualizing the density distributions of empirical and theoretical align-

ment ratings, faceted by the six most prevalent keywords in the dataset: learning, cognition, motivation, attitude, attention, and emotion. Each facet contains a pair of violin plots representing the distributions of empirical and theoretical alignment ratings, enabling direct comparison between these dimensions within each psychological construct. The violin plots combine box plots with kernel density plots to provide a comprehensive portrayal of the distributions, including their central tendencies and spreads."

The data reveal overall consistency across the different topics in psychology, as indicated by the keywords, yet there are important differences. For empirical alignment ratings, the means range from 7.33 in 'cognition' to 7.83 in 'learning,' indicating uniformly high empirical alignment. Standard deviations vary slightly, with the lowest being 1.08 in 'learning' and the highest at 1.81 in 'cognition,' reflecting relatively concentrated rating distributions within each subfield. Theoretical alignment ratings follow a similar pattern, with means ranging from 7.46 in 'cognition' to 8.03 in 'learning,' suggesting robust theoretical alignment. Standard deviations are tightly clustered, spanning from 1.00 in 'learning' to 1.83 in 'cognition.' These findings align with our prior discussion, suggesting that the efficacy of the AI is determined not by the tier of the journal but rather by the nature of the content published within the journal.

To identify the topics where the AI demonstrated the least proficiency, we applied a topic model to the articles where the AI scored 5 or below on at least one of the two alignment dimensions. Our analysis revealed three key topics: 'Visual Perception, Memory, and Psychological Processes,' 'Prosocial Behavior and Cooperation in Societies,' and 'Sensitivity and Perception in Social Interactions and Emotions.' These topics, characterized by complex, multifaceted psychological phenomena and highly context-dependent variables, suggest areas where current AI capabilities face significant challenges. Conversely, the AI showed greater proficiency in topics such as 'Visual Working Memory Experiments,' 'Linguistics and Cognitive Processing in Language Learning,' and 'Decision Making and Choice Models.' This dichotomy indicates that the AI's effectiveness is more pronounced in domains with well-defined cognitive processes and less so in those requiring a nuanced understanding of complex human behavior and social dynamics.

Discussion

Our research demonstrates that advancements in AI have propelled these systems far beyond their initial conception as mere statistical models 'parroting' large-scale datasets. Instead, they now exhibit a remarkable capacity to emulate the intricate intuition and reasoning processes that are hallmarks of human expertise.
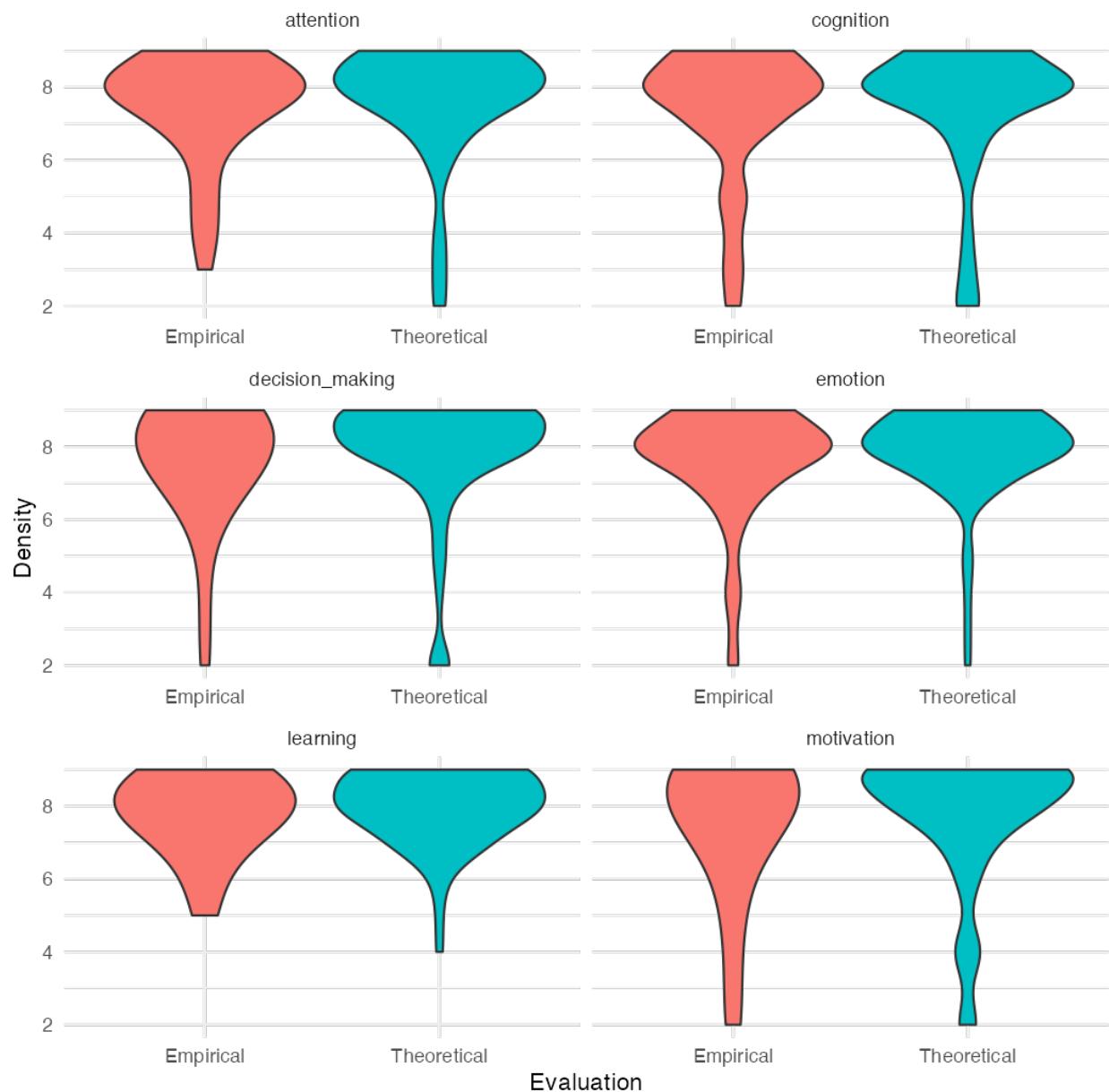
Figure 4: Violin Plots of Empirical and Theoretical Alignment Ratings by Keyword

Note: This figure features a series of violin plots that display the density distributions of empirical and theoretical alignment ratings on a nine-point scale, segmented by six significant keywords: learning, cognition, motivation, attitude, attention, and emotion. Each keyword is represented as a separate facet containing a pair of violins for empirical and theoretical alignments, allowing for a direct comparison between these two dimensions within each psychological construct.

This leap in capability can largely be attributed to extensive pre-training, during which AI assimilates a wide array of knowledge. Such a profound base of conceptual knowledge equips AI with the ability to undertake sophisticated theoretical extrapolations and deductions, developing a generalizable deductive prowess that closely mirrors the acumen of human experts, even in specialized fields like psychology, and in tasks where the AI has not been specifically trained. It challenges the traditional view that statistical models are only suitable for mechanical tasks like hypothesis testing, rather than creative endeavors like hypothesis generation and experimental design (Rai et al. 2019).

Crucially, our findings reveal that AI has developed the ability to dynamically and seamlessly adapt to entirely new contexts and scenarios. The origin of these capabilities remains an open question, as our methodology pioneers in exposing AI to both novel concepts and theories (i.e., novel conceptual knowledge), and novel application scenarios. This marks a significant departure from prior, state-of-the-art AI measurement approaches that either reword and reimagine existing concepts and theories in novel scenarios (Grinnell et al. 2023) or assess creativity through the administration of standardized tests such as the Torrance Tests of Creative Thinking (Guzik et al. 2023). While these traditional methods have their merits, notably in directly comparing the abilities of humans and AI, they primarily explore creativity within the confines of low knowledge complexity. For example, they are designed to evaluate divergent thinking skills based on everyday concepts, exemplified by questions like, "If all schools were abolished, what would you do to try to become educated?" In contrast, our study investigates creativity in scenarios of high knowledge complexity, asking the AI to reason about abstract constructs such as 'eudaimonic well-being.'

Creativity is thought to be the last bastion against the encroachment of automation (Brynjolfsson and McAfee 2014). Yet, the data affirms the ability of AIs to perform sophisticated analysis, integration, and evaluation of academic theories—tasks traditionally reliant on creative problem-solving and advanced human expertise. These capabilities reposition AI as a crucial asset for scrutinizing literature, critiquing new theoretical propositions, and identifying inconsistencies and gaps—roles traditionally reserved for research associates and postdoctoral scholars.

This raises significant questions about the future of AI in research and its potential to reshape the landscape: As research assistantships and fellowships serve as critical pathways to academic careers, the integration of AI could herald transformative changes, with conventionally stable scholarly positions facing fresh technological disruption.

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