

Navigating the Jagged Technological Frontier: Field Experimental Evidence of the Effects of AI on Knowledge Worker Productivity and Quality*

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Abstract

The public release of Large Language Models (LLMs) has sparked tremendous interest in how humans will use Artificial Intelligence (AI) to accomplish a variety of tasks. In our study conducted with Boston Consulting Group, a global management consulting firm, we examine the performance implications of AI on realistic, complex, and knowledge-intensive tasks. The pre-registered experiment involved 758 consultants comprising about 7% of the individual contributor-level consultants at the company. After establishing a performance baseline on a similar task, subjects were randomly assigned to one of three conditions: no AI access, GPT-4 AI access, or GPT-4 AI access with a prompt engineering overview. We suggest that the capabilities of AI create a “jagged technological frontier” where some tasks are easily done by AI, while others, though seemingly similar in difficulty level, are outside the current capability of AI. For each one of a set of 18 realistic consulting tasks within the frontier of AI capabilities, consultants using AI were significantly more productive (they completed 12.2% more tasks on average, and completed tasks 25.1% more quickly), and produced significantly higher quality results (more than 40% higher quality compared to a control group). Consultants across the skills distribution benefited significantly from having AI augmentation, with those below the average performance threshold increasing by 43% and those above increasing by 17% compared to their own scores. For a task selected to be outside the frontier, however, consultants using AI were 19 percentage points less likely to produce correct solutions compared to those without AI. Further, our analysis shows the emergence of two distinctive patterns of successful AI use by humans along a spectrum of human-AI integration. One set of consultants acted as “Centaur,” like the mythical half-horse/half-human creature, dividing and delegating their solution-creation activities to the AI or to themselves. Another set of consultants acted more like “Cyborgs,” completely integrating their task flow with the AI and continually interacting with the technology.

1 Introduction

The capabilities of Artificial Intelligence to produce human-like work have improved rapidly, especially since the release of OpenAI's ChatGPT, one of several Large Language Models (LLMs) that are widely available for public use. As AI capabilities overlap more with those of humans, the integration of human work with AI poses new fundamental challenges and opportunities, in particular in knowledge-intensive domains. In this paper, we examine this issue using randomized controlled field experiments with highly skilled professional workers. Our results demonstrate that AI capabilities cover an expanding, but uneven, set of knowledge work we call a "jagged technological frontier." Within this growing frontier, AI can complement or even displace human work; outside of the frontier, AI output is inaccurate, less useful, and degrades human performance. However, because the capabilities of AI are rapidly evolving and poorly understood, it can be hard for professionals to grasp exactly what the boundary of this frontier might be at a given. We find that professionals who skillfully navigate this frontier gain large productivity benefits when working with the AI, while AI can actually decrease performance when used for work outside of the frontier.

Though LLMs are new, the impact of other, earlier forms of AI have been the subject of considerable scholarly discussion (e.g., [Brynjolfsson et al. \(2018\)](#); [Furman and Seamans \(2019\)](#); [Puranam \(2021\)](#)). Because of the limitations of these earlier forms of AI, nonroutine tasks that were difficult to codify seemed protected from automation ([Autor et al., 2003](#); [Acemoglu and Restrepo, 2019](#)), especially as previous waves of technology had mostly automated lower-skilled occupations ([Goldin and Katz, 1998](#)). The release of ChatGPT in November, 2022 changed both the nature and urgency of the discussion. LLMs proved unexpectedly capable at creative, analytical, and writing tasks, including scoring at top levels at graduate and professional examinations ([Girotra et al., 2023](#); [Geerling et al., 2023](#); [Kung et al., 2023](#); [Boussioux et al., 2023](#)). This represented an entirely new category of automation, one whose abilities overlapped with the most creative, most educated, and most highly paid workers ([Eloundou et al., 2023](#)).

Studies of previous generations of AI ([Brynjolfsson et al., 2023](#)) and controlled

experiments on the impact of recently released LLMs (e.g., [Noy and Zhang \(2023\)](#); [Choi and Schwarcz \(2023\)](#)) suggest that these systems can have a large impact on worker performance. In our study, we focus on complex tasks, selected by industry experts to replicate real-world workflows as experienced by knowledge workers. Most knowledge work includes this sort of flow, a set of interdependent tasks, some of which may be good fit for current AI, while some are not. We examine both kinds of tasks, and build on recent studies to suggest ways of understanding the rapidly evolving impact of AI on knowledge workers, under which circumstances organizations may benefit, and how this might change as the technology advances.

This is important because understanding the implications of LLMs for the work of organizations and individuals has taken on urgency among scholars, workers, companies, and even governments ([Agrawal et al., 2018](#); [Iansiti and Lakhani, 2020](#); [Berg et al., 2023](#)). Previous forms of AI led to considerable debate in the literature around how and whether professionals should adopt AI for knowledge work ([Anthony et al., 2023](#)) and the potential impact this might have on organizations ([Raisch and Krakowski, 2021](#); [Glaeser et al., 2021](#); [Brynjolfsson et al., 2021](#)). Some scholars focused on the potential for AI to help professionals improve their effectiveness and efficiency ([DeStefano et al., 2022](#); [Balakrishnan et al., 2022](#); [Valentine and Hinds, 2023](#)). Others demonstrated that, for critical tasks, it can be risky for professionals to use AI ([Lebovitz et al., 2021](#)), especially black-boxed (e.g., [Lebovitz et al. \(2022\)](#); [Waardenburg et al. \(2022\)](#)), and showed how professionals are struggling to use it effectively ([Pachidi et al., 2021](#); [Van den Broek et al., 2021](#)). Finally, another group of researchers argued that the “algorithmic management” afforded by AI can create negative personal impacts for professionals ([Kellogg et al., 2020](#); [Möhlmann et al., 2021](#); [Tong et al., 2021](#)) and raise accountability and ethical questions ([Choudhury et al., 2020](#); [Cowgill et al., 2020](#); [Rahman et al., 2024](#)). Yet, most of the studies predate ChatGPT, and investigate forms of AI designed to produce discrete predictions based on past data. These systems are quite different from LLMs.

Specifically, outside of their technical differences from previous forms of machine learning, there are three aspects of LLMs that suggest they will have a much more rapid, and widespread, impact on work. The first is that LLMs have surprising

capabilities that they were not specifically created to have, and ones that are growing rapidly over time as model size and quality improve. Trained as general models, LLMs nonetheless demonstrate specialist knowledge and abilities as part of their training process and during normal use (Singhal et al., 2022; Boiko et al., 2023). While considerable debate remains on the concept of emergent capabilities from a technological perspective (Schaeffer et al., 2023), the effective capabilities of AIs are novel and unexpected, widely applicable, and are increasing greatly in short time spans. Recent work has shown that AI performs at a high level in professional contexts ranging from medicine to law (Ali et al., 2023; Lee et al., 2023), and beats humans on many measures of innovation (Boussieux et al., 2023; Girotra et al., 2023). And, while score performance on various standardized academic tests is an imperfect measure of LLM capabilities, it has been increasing substantially with each generation of AI models (OpenAI, 2023).

The general ability of LLMs to solve domain-specific problems leads to the second differentiating factor of LLMs compared to previous approaches to AI: their ability to directly increase the performance of workers who use these systems, without the need for substantial organizational or technological investment. Early studies of the new generation of LLMs suggest direct performance increases from using AI, especially for writing tasks (Noy and Zhang, 2023) and programming (Peng et al., 2023), as well as for ideation and creative work (Boussieux et al., 2023; Girotra et al., 2023). As a result, the effects of AI are expected to be higher on the most creative, highly paid, and highly educated workers (Eloundou et al., 2023; Felten et al., 2023).

The final relevant characteristic of LLMs is their relative opacity. This extends to the failure points of AI models, which include a tendency to produce incorrect, but plausible, results (hallucinations or confabulations), and to make other types of errors, including in math and when providing citations. The advantages of AI, while substantial, are similarly unclear to users. It performs well at some jobs, and fails in other circumstances in ways that are difficult to predict in advance. Contributing further to the opacity is that the best ways to use these AI systems are not provided by their developers and appear to be best learned via ongoing user trial-and-error and the sharing of experiences and heuristics via various online forums like user groups, hackathons, Twitter feeds and YouTube channels.

Taken together, these three factors – the surprising abilities of LLMs, their ability to do real work with virtually no technical skill required of the user, and their opacity and unclear failure points – suggest that the value and downsides of AI may be difficult for workers and organizations to grasp. Some unexpected tasks (like idea generation) are easy for AIs, while other tasks that seem to be easy for machines to do (like basic math) are challenges for some LLMs. This creates a “jagged Frontier,” where tasks that appear to be of similar difficulty may either be performed better or worse by humans using AI. Due to the “jagged” nature of the frontier, the same knowledge workflow of tasks can have tasks on both sides of the frontier, see Figure 1. The future of understanding how AI impacts work involves understanding how human interaction with AI changes depending on where tasks are placed on this frontier, and how the frontier will change over time. Investigating how humans navigate this jagged frontier, and the subsequent performance implications, is the focus of our work.

We collaborated with a global management consulting firm (Boston Consulting Group - BCG) and advised them on designing, developing, and executing two pre-registered randomized experiments to assess the impact of AI on high human capital professionals. Subsequently, the author team received the data that the company collected for the purpose of this experiment and conducted the analysis presented in this paper. The study was structured in three phases: an initial demographic and psychological profiling, a main experimental phase involving multiple task completions, and a concluding interview segment. We tested two distinct tasks: one situated outside the frontier of AI capabilities and the other within its bounds. The experiment aimed to understand how AI integration might reshape the traditional workflows of these high human capital professionals.

Our results show that this generation of LLMs are highly capable of causing significant increases in quality and productivity, or even completely automating some tasks, but the actual tasks that AI can do are surprising and not immediately obvious to individuals or even to producers of LLMs themselves. Because this frontier is expanding and changing, the overall results suggest that AI will have a large impact on work, one which will increase with LLM capabilities, but where the impacts occur will be uneven.

2 Methods

We collected data from two randomized experiments to assess the causal impact of AI, specifically GPT-4 – the most capable of the AI models at the time of the experiments (Spring 2023) – on high human capital professionals working traditionally without AI.¹ We pre-registered our study, detailing the design structure, the experimental conditions, the dependent variables, and our main analytical approaches.² Our aim was to determine how introducing this AI into the tasks of highly-skilled knowledge workers might augment, disrupt, or influence their traditional workflows.

BCG individual contributor consultants around the world were offered the opportunity to spend 5 hours working on this experiment to evaluate the impact of AI on their activities. Approximately 7% of BCG's global individual contributor consultants' cohort engaged in and completed the experiment.

The experiment was structured into three distinct phases. Initially, consultants entered the study by completing a survey that captured their demographic and psychological profiles, as well as details about their role within the company. A few weeks after enrolling, participants received a link to complete the main experimental phase. This phase commenced with a pre-task survey, followed by the tasks detailed subsequently, and concluded with a post-task survey. In the final phase, participants were interviewed to share their experiences and perspectives on the role of AI in their profession.

In the first phase, we administered an enrollment survey to gather information about potential participants.³ This survey captured details such as office location, internal affiliation, and tenure at BCG. Participants also completed psychological assessments, specifically providing insights into their Big 5 personality traits (Soto and John, 2017), innovativeness (Agarwal and Prasad, 1998), self-perceived creativity (Miron-Spektor et al., 2004), and paradox mindset (Miron-Spektor et al., 2018). Furthermore, the survey included a short section on their reading habits (including their familiarity with

¹The project has received IRB approval, IRB23-0392.

²Pre-registration completed on Open Science Foundation, osf.io/ytaev. The pre-registration is available from the authors upon request and will be made publicly available after article acceptance or after the OSF embargo period has passed, whichever comes first

³Out of the 852 consultants who responded to the survey, 758 - about 89% - completed the experiment.

AI characters in fiction), and demographic details like gender, native language, and educational background. We utilized these data for stratified random assignment and as controls in our regression models, as described below.

The study encompassed 758 strategy consultants, each of whom completed the initial survey and experimental tasks. Each participant was assigned to one of two distinct experiments. Stratification of participants was based on multiple criteria, both between experiments and across experimental treatments. These criteria included gender, location, tenure at BCG, individual openness to innovation, and native English-speaking status. This information was collected with the survey administered during phase one, a few weeks before the main experiment.

In order to ensure genuine engagement and effort from participants, we incentivized their performance in the experiment. Participants who diligently participated in all aspects of the experiment were honored with an "office contribution" recognition, carrying financial implications related to their annual bonuses. Furthermore, to recognize and reward excellence, the top 20% of participants received additional recognition, and the top 5% was also awarded with a small gift. Executives at BCG reported that the recognition received by top participants was important because it was shared with the committee that oversees their career development and performance assessments.

Subjects were allocated to one of two distinct experiments, each involving a unique type of task, with no overlap between the groups. Both tasks were designed in collaboration with multiple people at BCG to represent some of the typical job activities encountered by individual contributor consultants. Approximately half of the participants (385 consultants) tackled a series of tasks where they were prompted to conceptualize and develop new product ideas, focusing on aspects such as creativity, analytical skills, persuasiveness and writing skills. The other half (373 consultants) engaged in business problem-solving tasks using quantitative data, customer and company interviews, and including a persuasive writing component. Both sets of tasks were developed to be realistic, and were designed with the input of professionals in the respective sectors. A senior level executive at the company commented on these tasks being "very much in line with part of the daily activities" of the subjects involved.

Notably, some forms of these tasks are also used by the company to screen job applicants, typically from elite academic backgrounds (including Ph.D.s), for their highly-coveted positions.

Both experiments followed a consistent structure. Initially, participants undertook a task without the aid of AI, establishing a baseline for performance and enabling within-subject analyses. Following this, participants were randomly assigned to one of three conditions to assess the influence of AI on their tasks, with these conditions being consistent across both experiments. The first group (a control condition) proceeded without AI support; the second (“GPT Only”) had the assistance of an AI tool based on GPT-4; and the third (“GPT + Overview”) not only utilized the same AI tool but also benefited from supplementary prompt engineering overview, which increased their familiarity with AI. These materials included instructional videos and documents that outlined and illustrated effective usage strategies.

Rather than relying on self-reported metrics or indirect indicators, we directly assessed participants’ skills through a task that closely mirrored the main experiment. In both experiments, we employ an assessment task that, while different from the experimental task, is highly comparable, ensuring a precise evaluation of skills for this specific task type.⁴ Our findings indicate that performance in the assessment task is a predictor of performance in the experimental task, allowing us to study the differential effects of introducing AI to participants of different skill levels.

Each task assigned to participants came with a specific time allocation. In the experiment using a task inside the frontier, the assessment task duration was set for 30 minutes, while the subsequent one was allotted 90 minutes. Conversely, in the outside-the-frontier experiment, both the first and second tasks were designated 60 minutes each, though participants could complete them earlier if they finished ahead of time. It is important to note that for the task inside the frontier, participants were required to remain on the task’s page for the entire duration of the task, and could not complete the exercise earlier. This approach ensured that our analysis for the inside-the-frontier tasks focused

⁴Dell’Acqua et al. (2023) adopts a comparable experimental framework to evaluate subjects’ competencies.

chiefly on the qualitative differences, rather than any timing improvements brought about by using AI. These timeframes were automatically enforced, with the experimental system advancing to the next question once the stipulated time for a task elapsed.

In every experimental task, subjects assigned to the AI conditions had access to a company platform. This platform, developed using the OpenAI API, facilitated an interactive experience with OpenAI's GPT-4, mirroring the dynamics of ChatGPT. It enabled the collection of all participants' prompts and AI's corresponding responses, providing a comprehensive view into the collaborative behaviors between subjects and AI. All subjects used the same version of the tool, accessing GPT-4 as available at the end of April, 2023, and using default system prompts and temperature.

Aside from the thematic differences, the tasks differed in another key way. While both were designed to be comparably complex and realistic, the first task was selected to be within the potential technological frontier of GPT-4. The second experiment was designed so that GPT-4 would make an error when conducting the analysis, ensuring the work fell just outside the frontier.

3 Results

3.1 Quality and Productivity Booster - Inside the Frontier

The inside-the-frontier experiment focused on creative product innovation and development. The initial assessment task asked participants to brainstorm innovative beverage concepts. From their set of ideas, they identified the most viable option and devised a comprehensive plan for its market debut. After this task, subjects moved to the main experimental phase and the context transitioned to the main experimental task.

In this experimental task, participants were tasked with conceptualizing a footwear idea for niche markets and delineating every step involved, from prototype description to market segmentation to entering the market. An executive from a leading global footwear company verified that the task design covered the entire process their company

typically goes through, from ideation to product launch.⁵ Participants responded to a total of 18 tasks (or as many as they could within the given time frame). These tasks spanned various domains. Specifically, they can be categorized into four types: creativity (e.g., “Propose at least 10 ideas for a new shoe targeting an underserved market or sport.”), analytical thinking (e.g., “Segment the footwear industry market based on users.”), writing proficiency (e.g., “Draft a press release marketing copy for your product.”), and persuasiveness (e.g., “Pen an inspirational memo to employees detailing why your product would outshine competitors.”). This allowed us to collect comprehensive assessments of quality. All tasks and details are reported in Appendix A.

In the experiment, the primary outcome variable is the quality of the subjects’ responses. To quantify this quality, we employed a set of human graders to evaluate each question that participants didn’t leave unanswered.⁶ Each response was evaluated by two human graders. We then calculated the mean grade assigned by humans to each question. This gave us 18 dependent variables (one per each question). We subsequently averaged these scores across all questions to derive a composite “Quality” score, which we use in our main analyses. As an additional assessment, we also utilized GPT-4, to independently score the subjects’ responses. Similarly to the human grades, we produced a score for each one of the 18 questions, and then a composite “Quality (GPT)” score.

Figure 2 uses the composite human grader score and visually represents the performance distribution across the three experimental groups, with the average score plotted on the y-axis. A comparison of the dashed lines and the overall distributions of the experimental conditions clearly illustrates the significant performance enhancements associated with the use of GPT-4. Both AI conditions show clear superior performance to the control group not using GPT-4.

Table 1 presents the results of the analyses using response quality as the dependent variable and highlights the performance implications of using AI. Columns 1, 2, and 3 utilize human-generated grades as the dependent variable, while Column 4 uses the

⁵The executive noted the only step missing from this exercise was an evaluation of how the new product integrates with the company’s existing product lines. As our experiment used a fictional company, we did not require participants to present their product suggestions in relation to existing ones.

⁶Graders were from BCG, or MBA students at a top program.

composite grades generated by GPT-4. Across all specifications, both treatments — GPT + Overview and GPT Only — demonstrate positive effects. In Column 1, GPT + Overview leads to a 1.75 increase in scores over the control mean of 4.1, which is a 42.5% increase; GPT Only led to a 1.56, or 38% increase. Notably, Columns 2, 3, and 4 incorporate performance metrics from the assessment task and the treatment coefficients they report remain very consistent. Column 4 uses GPT scores as the dependent variable, and shows coefficients of 1.34 for the GPT + Overview treatment and 1.21 for the GPT Only treatment over the control group, which are equal respectively to 18.6% and 16.8% increases in performance.⁷

The beneficial impacts of using AI remain consistent across all our specifications. We merged our AI treatments and used all our pre-registered quality variables as dependent variables. This included individual grades for each question as evaluated by humans, as well as grades evaluated by GPT-4, based on the three specifications outlined in Columns 1-3 of Table 1. This resulted in a comprehensive set of 108 regressions. All of these regressions showed a significant effect of introducing AI on consultants' performance. Figures 3 and 4 show 54 of these regressions each. Additionally, three dashed lines report the average effects of each regression. The mean effect size when comparing subjects using AI with a control with no GPT-4 access is 1.69 (a 46.6% increase over the control mean) when using human evaluations and 1.36 (20.2%) when using GPT-4 evaluations.

Another key observation from the table is the differential impact of the two AI treatments. Specifically, the GPT + Overview treatment consistently exhibits a more pronounced positive effect compared to the GPT Only treatment. The bottom of the table displays a p-value that tests whether the effects of receiving GPT + Overview were equivalent to those of being assigned to GPT Only, showing this value to be below or around the conventional 5% threshold in all specifications. This underscores the importance of the added overview in enhancing the efficacy of AI assistance. However, we should note that the overview increased “retainment” (i.e., copying and pasting the GPT-4 output), and retainment itself was associated with better performance.⁸ The table

⁷These percentage improvements are relatively lower also because GPT-4 tends to be a more lenient grader and scores our control baseline higher.

⁸Appendix C provides further details.

also highlights various other factors, such as gender, native English proficiency, tenure, location, and tech openness, and their influence on the outcomes.⁹

Table 2 presents the results related to the percentage of task completion by subjects, which is the dependent variable in this analysis. Across Columns 1, 2, and 3, both treatments — GPT + Overview and GPT Only — demonstrate a positive effect on task completion. On average, these coefficients indicate a 12.2% increase in completion rates.¹⁰ The control group completed on average 82% of their tasks, while the GPT + Overview condition completed about 93% and GPT Only about 91%. Column 2 incorporates the performance metric from the assessment, and Column 3 further extends the analysis by including the same set of controls as in Table 1. The coefficients suggest that the integration of AI tools enhances the rate of task completion very significantly, at the same time as it increases quality.

Figure 5 presents an important trend: the most significant beneficiaries of using AI are the bottom-half-skill subjects, consistent with findings from Noy and Zhang (2023) and Choi and Schwarcz (2023).¹¹ By segmenting subjects exposed to one of the two AI conditions into two distinct categories — top-half-skill performers (those ranking in the top 50% on the assessment task) and bottom-half-skill performers (those in the bottom 50%) — we observed performance enhancements in the experimental task for both groups when leveraging GPT-4. When comparing the two groups, though, we see the bottom-half-skill performers exhibited the most substantial surge in performance, 43%, compared to the top-half-skill subjects, 17%. Note that the top-half-skill performers also receive a significant boost, although not as much as the bottom-half-skill performers.

For the task inside the frontier, we did not allow any subjects to complete the task before the allotted time was over. Instead, their final question was an especially long

⁹We employ binary variables for all these factors. "Female" is set to 1 if a subject identifies as female and 0 otherwise. "English Native" is 1 if a subject claims native proficiency in English and 0 otherwise (nearly every subject indicates either Native or Advanced proficiency in English). "Low Tenure" is 1 if a subject has been with BCG for a year or less, and 0 otherwise. "Location" is 1 if a subject's office is located in Europe or the Middle East, and 0 otherwise. Lastly, "Tech Openness" is 1 if the subject expressed a higher receptivity to technology in their enrollment survey, and 0 otherwise.

¹⁰When directly comparing the two AI treatments at the bottom of the table, the difference in their impacts is not statistically significant.

¹¹It is important to note that "higher-skill" and "lower-skill" here are relative. All these consultants would appear to be extremely high-skill in most other real-world contexts.

one asking them to “synthesize the insights you have gained from the previous questions and create an outline for a Harvard Business Review-style article of approximately 2,500 words.” However, while participants were required to take the full time allotted to this task, we nevertheless tracked the amount of time that they took to reach this last question, having completed the first 17 questions. Table 3 uses this Timing variable as the dependent variable. The GPT + Overview treatment makes subjects faster by 1129 seconds (18.8 minutes or 22.5% faster than the control), while the GPT Only treatment reduces time spent on the first 17 questions by 1388 seconds (23.13 minutes or 27.63% faster than the control).

Exploring the variation in content generated by subjects, our focus was on understanding the diversity of their responses in relation to others. By employing Google’s Universal Sentence Encoder (USE), we semantically analyzed the ideas presented by subjects in the first question of the inside-the-frontier experiment (“Generate ideas for a new shoe aimed at a specific market or sport that is underserved. Be creative, and give at least 10 ideas”). Our findings indicate that while subjects using AI produce ideas of higher quality, as discussed in the previous sections, there is a marked reduction in the variability of these ideas compared to those not using AI. This suggests that while GPT-4 aids in generating superior content, it might lead to more homogenized outputs. Figure 6 shows the distribution of similarity across experimental groups. For a detailed analysis, refer to Appendix D.

Our results reveal significant effects, underscoring the prowess of AI even in tasks traditionally executed by highly skilled and well-compensated professionals. Not only did the use of AI lead to an increase in the number of subtasks completed by an average of 12.5%, but it also enhanced the quality of the responses by an average of more than 40%. These effects support the view that for tasks that are clearly within its frontier of capabilities, even those that historically demanded intensive human interaction, AI support provides huge performance benefits.

3.2 Quality Disruptor - Outside the frontier

In refining the task within the frontier and recognizing the substantial quality and productivity gains from AI integration, we sought a task that AI couldn't easily complete through simple copying and pasting of our instructions as a prompt. We designed the task outside the frontier using as a starting point the type of business cases that BCG uses for its highly competitive job interviews. Our goal was to design a task where consultants would excel, but AI would struggle without extensive guidance. After several iterations, we settled on a task based on an existing business case that used data on a spreadsheet, as well as a file presenting interviews with company insiders, which were adjusted and adapted to the goals of this experiment. To be able to solve the task correctly, participants would have to look at the quantitative data using subtle but clear insights from the interviews. While the spreadsheet data alone was designed to seem to be comprehensive, a careful review of the interview notes revealed crucial details. When considered in totality, this information led to a contrasting conclusion to what would have been provided by AI when prompted with the exercise instructions, the given data, and the accompanying interviews.

In this second experiment, the primary objective was for subjects to offer actionable strategic recommendations to a hypothetical company. First, participants worked on the assessment task, where they had to analyze the company's channel performance. Using insights from interviews and financial data, participants were asked to provide information and informed advice to the CEO. Their recommendations were to pinpoint which channel held the most potential for growth.

As subjects completed their assessment task, they moved to the main experimental task. The focus transitioned from the examination of the company's distribution channels to brand analysis, as subjects had to analyze the company's brand performance. Similarly to the assessment task, participants used insights from interviews and financial data to provide recommendations for the CEO. Their recommendations were to pinpoint which brand held the most potential for growth. Additionally, participants were also expected to suggest actions to improve the chosen brand, regardless of the exact brand they had

chosen. Details of these tasks are reported in Appendix A.

For this task outside the frontier, our primary metric of evaluation is 'correctness.' This is represented as a binary variable, where a value of '1' indicates that subjects provided the accurate recommendation, and '0' signifies otherwise. Figure 7 visually presents the correctness percentages across different groups, highlighting a noticeable dip in performance among the AI treatment groups when juxtaposed with the control group. Subjects in the control group were correct about this exercise about 84.5% of the time, while the AI conditions scored at 60% and 70% (for an average decrease of 19 percentage points when combining the AI treatment conditions and comparing them to the control condition).

Table 4 delves into the impact of the AI treatments on the correctness of tasks in the outside-the-frontier experiment using linear regressions with correctness as a binary dependent variable. Both AI treatments— GPT + Overview and GPT Only — show a significant negative impact, with the GPT + Overview group experiencing a more pronounced decrease (24 percentage points versus 13 percentage points). Column 2 introduces the performance metric from the assessment, while Column 3 further refines the analysis by incorporating the same set of controls as in Tables 1 and 2. When directly comparing the two treatments, the difference in their impacts is statistically significant at the 10% threshold across specifications.

Table 5 examines the influence of the AI treatments on the time taken by participants to complete tasks in the outside-the-frontier experiment. The dependent variable here is "Timing," representing the duration subjects spent on the task calculated in seconds. Column 2 further refines the analysis by incorporating the same set of controls as in Table 1. Both AI treatments — GPT + Overview and GPT Only — indicate a reduction in the time spent, more than 11 minutes for GPT + Overview (a 30% decrease in timing over the control mean), and more than 6 minutes for GPT Only (a decrease of 18%) when compared to the control. When we compare the two coefficients, we find that GPT + Overview shows a more substantial decrease in time, and one that is statistically significant, compared to the GPT Only group.

Table 6 further examines the quality of recommendations provided by subjects in

the outside-the-frontier experiment. The dependent variable, 'Recommendation Quality,' measures the quality of the recommendations given. These were scored (on a 1-10 scale) by two different sets of human graders (one of BCG consultants not involved in the experiment, and the other of business school students with grading experience) following a simple rubric, developed by the authors relying on their experience in consulting (see Appendix B for the full rubric). Looking at Column 1, the treatment GPT + Overview leads to a 1.47 greater score (25.1% increase over the control mean), while GPT Only increases the score by 1.05 (17.9% over the control mean). Across all specifications, subjects using AI (both GPT + Overview and GPT Only) consistently outperformed those not using AI in terms of recommendation quality, regardless of the correctness of their answer. When we control for various factors (as in Table 1) in columns 2, 3, and 4, the positive impact of AI remains robust. This result holds true regardless of the correctness of the subjects' answers, as evidenced in columns 3 and 4. Column 3 reports the same regression in column 2 only for the subset of participants whose answers were incorrect, while column 4 does the same for the subset of participants whose answers were correct. In both instances, the effects of using AI are positive.

Figure 8 shows the quality of recommendations for people who were wrong in their answers and for those who were right (Figure 8). Both distributions show a clear shift for the experimental groups using AI. That is, the quality of the recommendation about a business problem-solving case increased, regardless of whether the underlying recommendation was correct or not. This finding underscores the multifaceted ways in which AI can influence performance in a workflow among highly skilled professionals.

3.3 Navigating the frontier

The experiments show that the shape and position of the frontier are vital to understanding the impact of AI on work. On tasks within the frontier, AI significantly improved human performance. Outside of it, humans relied too much on the AI and were more likely to make mistakes. Not all users navigated the jagged frontier with equal adeptness. While some completed their task incorrectly, others showcased a remarkable ability to harness the power of AI effectively. We conducted further analyses of the

strategies adopted by those who managed to perform correctly in the outside-the-frontier experimental task while using LLMs. Understanding the characteristics and behaviors of these participants may prove important as organizations think about ways to identify and develop talent for effective collaboration with AI tools.

We identified two predominant models that encapsulate their approach.

The first is Centaur behavior. Named after the mythical creature that is half-human and half-horse, this approach involves a similar strategic division of labor between humans and machines closely fused together.¹² Users with this strategy switch between AI and human tasks, allocating responsibilities based on the strengths and capabilities of each entity. They discern which tasks are best suited for human intervention and which can be efficiently managed by AI.

The second model we observed is Cyborg behavior.¹³ Named after hybrid human-machine beings as envisioned in science fiction literature, this approach is about intricate integration. Cyborg users don't just delegate tasks; they intertwine their efforts with AI at the very frontier of capabilities. This strategy might manifest as alternating responsibilities at the subtask level, such as initiating a sentence for the AI to complete or working in tandem with the AI.

We are continuing to examine these behaviors using the experimental task's GPT logs and rich qualitative data gathered from the experiments in order to create an emerging understanding of these behaviors. We are also investigating the impact of these behaviors on performance. Appendix E further explores these behaviors.

4 Discussion

In this paper, we study the integration of AI with a jagged capability frontier into contemporary human real-world, high-end knowledge work tasks. We use a randomized field experiment to illuminate the dual role of AI as both a booster, enhancing efficiency and productivity, and a disruptor, negatively impacting performance in tasks outside its

¹²This term was prominently used by chess champion Garry Kasparov to describe how humans and AI might collaborate in chess.

¹³Clynes and Kline (1960) first proposed this term.

frontier. Our findings underscore the transformative potential of AI and offer insights into harnessing its capabilities for optimal outcomes. A crucial feature of our experiment was the availability of our experimental subjects. Specifically, we tapped into a high human capital population, with participants who were not only highly skilled but also engaged in tasks that closely mirrored part of their professional activities.

We found that the utility of AI can fluctuate over the course of a professional's workflow, with some tasks falling inside while others fall outside of the frontier. For tasks inside the frontier, these findings carry large performance implications. Across 18 realistic business tasks, AI significantly increased performance and quality for every model specification, increasing speed by more than 25%, performance as rated by humans by more than 40%, and task completion by more than 12%. Further, it operated in a way that benefitted bottom-half performers the most, though all users benefitted from AI. Thus, AI seems to both level performance differences across levels of ability and raise the quality of work for inside-the-frontier tasks. These findings suggest a need to understand how work can be organized to better integrate AI. Tasks outside the AI frontier also present opportunities for individuals to operate as either cyborgs or centaurs. Cyborgs integrate AI and human capabilities at a granular, sub-task level, while centaurs strategically delegate between human and AI sub-tasks. In our sample, we observed these two behaviors (see Appendix E). It is clear that the best approaches to using AI are not fully understood and need to be deeply examined by scholars and practitioners.

It was only when we identified tasks outside the frontier that we saw performance decreases as a result of AI. On those tasks, this study highlights the importance of validating and interrogating AI ([Lebovitz et al., 2022](#)) and of continuing to exert cognitive effort and experts' judgment when working with AI ([Dell'Acqua, 2022](#)). Professionals who had a negative performance when using AI tended to blindly adopt its output and interrogate it less ("unengaged interaction with AI" [Lebovitz et al. \(2022\)](#)). Appendix B presents a "retainment" score measuring how common blind adoption was among our subjects. These findings raise questions regarding when and how to know whether to trust LLMs ([Glikson and Woolley, 2020](#)) in particular as AI tools impact employees' performance and their subsequent evaluation ([Teodorescu et al., 2021](#); [Gkeredakis, 2022](#)).

For AI designers and companies, these findings offer an important path for designing AI tools and for building navigation capabilities of the users (Lebovitz et al., 2021; Valentine and Hinds, 2023).

More broadly, these findings raise questions regarding using AI for high-risk tasks and responsible AI, a topic that is highly debated by AI policymakers and academics (Waardenburg et al., 2022; Rahman et al., 2024; *AI Act*, 2023). An immediate danger emerging from these findings, for instance, is that people will stop delegating work inside the frontier to junior workers, creating long-term training deficits (Beane, 2019).¹⁴ Navigating the frontier requires expertise, which will need to be built through formal education (Osterman, 2011; Myers and Kellogg, 2022), on-the-job training (Kellogg et al., 2021), and employee-driven upskilling (Leonardi and Neeley, 2022; Iansiti and Nadella, 2022).

In this study, we focus on the individual level of analysis but, as we had such a large number of professionals from within a single organization (BCG), this study clearly offers organization-level implications as well. First, our findings bring in a nuanced response to the ongoing debate on whether organizations should adopt AI for high-end knowledge work. The results suggest that this debate should move beyond the dichotomous decision of adopting or not AI and instead focus on the knowledge workflow and the tasks within it, and in each of them, evaluate the value of using different configurations and combinations of humans and AI. This will require rethinking collaboration between humans and AI (Anthony et al., 2023; Faraj and Leonardi, 2022; Feuerriegel et al., 2022), how new roles will emerge and be created (Barrett et al., 2012; Allen and Choudhury, 2022; Kellogg, 2022; Sergeeva et al., 2020), how adoption will be shaped by stakeholders in the organization and beyond (Sendak et al., 2020; Hillebrand et al., 2023), new capabilities and strategies (Iansiti and Lakhani, 2020) and new forms of organizing (Bailey et al., 2022; Beane and Leonardi, 2022). Moreover, the significant impact on creativity suggests AI should play a role in the future of organizing for innovation (Kittur et al., 2019; Amabile, 2020; Raj et al., 2023; Lifshitz-Assaf and Lazar, 2023; Boussioux et al., 2023).

The potential for diminished diversity of ideas stemming from AI usage could

¹⁴AI could also play a role in supporting human training (Gaessler and Piezunka, 2023).

pose challenges for organizations (e.g., [Page \(2019\)](#) (see appendix D)). As companies increasingly integrate AI into their operations, they must consider whether employing a variety of AI models, possibly multiple LLMs, or increased human-only involvement, could counteract this homogenization (with the associated tradeoffs). This underscores the significance of maintaining a diverse AI ecosystem. Moreover, the optimal AI strategy might vary based on a company's production function. While some organizations might prioritize consistently high average outputs, others might value maximum exploration and innovation. Finally, there may be some general equilibrium considerations to incorporate. Outputs like grants or articles might indeed be of superior quality when AI-assisted. However, in a competitive landscape where many are leveraging AI, outputs generated without AI assistance might stand out and achieve notable success due to their distinctiveness. Clearly, the interplay between the quality and variability of ideas is intricate, and further investigation is essential to unpack the nuances and implications of these results.

Finally, we note that our findings offer multiple avenues for interpretation when considering the future implications of human/AI collaboration. Firstly, our results lend support to the optimism about AI capabilities for important high-end knowledge work tasks such as fast idea generation, writing, persuasion, strategic analysis, and creative product innovation. In our study, since AI proved surprisingly capable, it was difficult to design a task in this experiment outside the AI's frontier where humans with high human capital doing their job would consistently outperform AI. However, navigating AI's jagged capabilities frontier remains challenging. Even for experienced professionals engaged in tasks akin to some of their daily responsibilities, this demarcation is not always evident. As the boundaries of AI capabilities continue to expand, often exponentially, it becomes incumbent upon human professionals to recalibrate their understanding of the frontier and for organizations to prepare for a new world of work combining humans and AI. Overall, AI seems poised to significantly impact human cognition and problem-solving ability. Similarly to how the internet and web browsers dramatically reduced the marginal cost of information sharing, AI may also be lowering the costs associated with human thinking and reasoning, with potentially

broad and transformative effects.

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