When and How Artificial Intelligence Augments Employee Creativity

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Abstract

Can artificial intelligence (AI) assist human employees in increasing employee creativity? Drawing on research on AI-human collaboration, job design, and employee creativity, we examine AI assistance in the form of a sequential division of labor within organizations: in a task, AI handles the initial portion which is well-codified and repetitive, and employees focus on the subsequent portion involving higher-level problem-solving. First, we provide causal evidence from a field experiment conducted at a telemarketing company. We find that AI assistance in generating sales leads, on average, increases employees' creativity in answering customers' questions during subsequent sales persuasion. Enhanced creativity leads to increased sales. However, this effect is much more pronounced for higher-skilled employees. Next, we conducted a qualitative study using semi-structured interviews with the employees. We found that AI assistance changes job design by intensifying employees' interactions with more serious customers. This change enables higher-skilled employees to generate innovative scripts and develop positive emotions at work, which are conducive to creativity. By contrast, with AI assistance, lower-skilled employees make limited improvements to scripts and experience negative emotions at work. We conclude that employees can achieve AI-augmented creativity, but this desirable outcome is skill-biased by favoring experts with greater job skills.

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"We need to acquaint a generation of workers with technologies to take on the more mundane, repetitive portions of their jobs, and in turn elevate their decision-making roles within enterprises."

Forbes Magazine, February 13, 2021[1]

INTRODUCTION

In modern organizations, employee creativity, which enables employees to solve problems whose solutions have not yet been established (e.g., Zhou and George 2001), plays a vital role in increasing employee productivity and, thus, organizational performance (e.g., Anderson, Potocnik, and Zhou 2014). Can AI technology increase the creativity of human employees, thus generating "AI-augmented employee creativity"? This question has attracted significant interest from industry experts in terms of both technology adoption and human resource management. A promising vision for organizations is to use AI to assist human employees by "freeing [them] for higher-level" problem solving (Wilson and Daugherty 2018, p. 6). One speculation is that AI can increase employee creativity as "humans and bots work together, with bots taking care of the heavy lifting, so humans can focus on the creative [part]" (O'Carroll 2017). However, there is a lack of theoretical foundation and systematic empirical evidence of whether AI can indeed assist employees in creatively solving higher-level problems and the critical conditions that must be met for this desirable outcome.

We address this gap by studying AI-human collaboration in a sequential division of labor (Puranam 2020), which entails assigning the initial well-codified and repetitive portions of a task to AI and the subsequent higher-level problem-solving portions of the same task to human employees. First, we argue that this form of AI assistance changes the human employees' job design. On this basis, we draw on the insights developed by job characteristic models (e.g., Hackman, Oldham, Janson, and Purdy 1975; Elsbach and Hargdon 2006; Chae and Choi 2018) and research on employee creativity (e.g., Amabile, Conti, Coon, Lazenby, and Herron 1996; Zhou and Shalley 2003) to develop two competing implications for whether this form of AI assistance increases employee creativity. We then identify employees' job skills, i.e.,

1 https://www.forbes.com/sites/joemckendrick/2021/02/13/needed-people-to-put-the-intelligence-in-artificial-intelligence/?sh=434a86533160&mod=djemAIPro.

domain expertise in carrying out the tasks required by their jobs, as a critical condition. Thus, we hypothesize that this form of AI assistance is more likely to enable higher-skilled employees to find new, useful solutions for higher-level problems, thus demonstrating greater creativity. (It is important to clarify that we distinguish high- and low- skilled employees based on their varying expertise of performing the *same* task; we do *not* refer to employees who perform different tasks that require greater or lesser training.) We also argue that increasing employee creativity is critical for AI assistance to enhance organizational performance.

We employed a mixed-methods empirical approach. First, we provided causal evidence from a field experiment conducted by a major telemarketing company. The task involved making outbound calls to sell credit cards to customers, which comprised generating sales leads, a well-codified activity that an established AI conversational bot technology could perform, and subsequently persuading these sales leads to make purchases, which human sales agents performed. We used double randomization: 3,144 customers were randomly assigned to be served by AI human teams or human agents alone, and 40 human agents were randomly assigned to work in AI human teams or independently. To measure employee creativity, we used voice recognition and text mining analysis to process the audio recordings of agents' conversations during sales persuasion, identifying whether customer questions fell outside the scope of agents' training and whether agents successfully answered these untrained questions. We also observed whether customers applied for credit cards after the sales calls. The results show that, on average, agents with AI assistance were 2.33 times as successful in solving untrained questions as those without AI assistance, but the magnitude of this increase was much more pronounced for top agents—2.81 times that of bottom agents. Further, causal mediation analysis demonstrates that increased success in answering untrained questions is critical for AI-assisted agents to achieve higher customer purchase rates than those obtained independently.

Subsequently, we conducted semi-structured interviews with the 28 sales agents involved in the field experiment. The agents confirmed that AI assistance changed their job design by screening out uninterested customers, thereby intensifying their interactions with more serious customers. This change impacted agents' skills and psychology but with a distinct divergence based on the agent's job skills. Higher-skilled agents discussed several paths through which such a change enabled them to produce more innovative scripts to address untrained questions from customers. This change also engenders positive psychological outcomes for higher-skilled agents, including better mood, higher morale, a greater sense of freedom in their position, and a more positive view of the firm. In contrast, lower-skilled agents expressed that they had limited abilities to take advantage of the opportunities presented by this change to solve untrained questions and reported greater stress, a stronger sense of defeat, and lower morale. The findings corroborate and enrich our theory by generating deeper and more nuanced insights into the underlying mechanisms through which AI assistance affects employee creativity.

This paper makes the following contributions. First, by demonstrating that it is possible to use AI-human collaboration to increase employee creativity, thus achieving "AI-augmented employee creativity," this paper contributes to the fast-growing literature of "augmented intelligence," which focuses on creating complementary between AI and humans (Davenport and Kirby 2016, Raisch and Krakowski 2021; Lebovitz, Lifshitz-Assaf, and Levina, 2022). Despite being attractive, the idea of using AI and humans together for "co-creation" (e.g., Daugherty and Wilson 2018; Puranam 2020; Wilson and Daugherty 2018) remains broad and vague. We developed a concrete design using the sequential division of labor to create a complementary relationship between AI and human employees. In the literature on employee creativity, our study adds AI assistance to the toolbox that enables employees to solve problems in a novel and useful manner, thereby improving creativity at work. Moreover, based on theories of AI-human collaboration and job design, our analysis identified a deeper theoretical tension in generating AI-augmented employee creativity. This tension, and the critical scope conditions, are new to what we previously knew about how AI may affect employees' creativity at work.

Second, by delineating the critical conditions concerning employees' job skills, we highlight that AI-augmented creativity is *skill-biased*. Economic theory on skill-biased technology establishes that production technologies enable skilled labor to become more productive than unskilled labor (Card and DiNardo 2002). We reveal that AI technologies in non-production-related organizational contexts also exhibit this feature, but for different theoretical reasons—employees' job skills critically shape their cognitive abilities and psychological outcomes, which are conducive to creativity. This is a novel insight into employee creativity literature. Moreover, whereas the literature on AI adoption commonly considers human employees' job skills to enable them to compete in a "horse race" with AI (Choudhury, Starr, and Agarwal 2020), we expand this view by showing that job skills also shape how employees benefit from AI assistance. Finally, despite their benefits, skill-biased AI augmented intelligence raises serious questions about the dark side of AI adoption in organizations (Kellogg, Valentine, and Christin 2020).

Overall, the novel findings contribute to scholars' understanding of human-AI collaboration—namely, how redesigning a job to incorporate AI has implications for the creativity of a human worker. The findings are based on mixed methods: quantitative, experimental methods to identify a meaningful effect in the field, paired with qualitative methods for elucidating mechanisms.

THEORY AND HYPOTHESES

AI-Human Collaboration Changes Job Design

AI technologies have been implemented to conduct a fast-growing set of economic activities with higher accuracy, reliability, and scalability than humans (e.g., Balasubramanian et al. 2018; Balasubramanian et al. 2020). Current AI technologies are particularly effective in performing repetitive, well-codified tasks that follow clear, specific protocols and scripts (Choudhury et al. 2020; Berenthe, Gu, Recker, and Santhanam 2021). However, the current form of AI faces limitations in handling unscripted, higher-level, unstructured tasks (Brynjolfsson and McAfee 2014, Berenthe et al. 2021), partially because it does not have human-like creativity in generating new answers to unknown problems (O'Carroll 2017; Wilson and Daugherty 2018).

A division of labor between AI and humans may be plausible to leverage the relative strengths of AI and human employees (Puranam, 2020). Any successful division of labor entails breaking down the goal of achieving a particular organizational task into interdependent work sub-clusters (e.g., Milgrom and Roberts 1990). Such interdependence can manifest *sequentially* when the outcome of one subtask becomes the input for another or *in parallel* when subtasks jointly produce a common outcome (Christensen and Knudsen 2020).[2]

In this study, we focus on the sequential division of labor; specifically, that AI handles the well-codified, repetitive portion of the task, whose outcomes are necessary inputs for subsequent higher-level problem-solving portions of the same task. This is a form of AI-human collaboration. In reality, many sequential multistage tasks exist. For example, in making sales, the sequential portions involve vetting potential customers' interests to generate sales leads and then persuading the leads to make a purchase (e.g., Debecker 2019; Kasan 2020a; Sabnis et al. 2013). In managing patients, the sequential components involve triaging by collecting information on patients to sort them into categories so that medical doctors can subsequently conduct more focused examinations and diagnoses (Longoni, Bonezzi, and Morewedge 2019). In the recruiting task, the sequential components entail prescreening to identify and exclude any poor fit for the firm based on basic information. Thus, subsequent in-depth interviews can focus on a smaller set of more targeted candidates (Chen and Li 2018; van den Broek et al. 2021).

Introducing such a division of labor between AI and human employees results in a structural change in the job design of human employees, with two key features: it lowers the workload on employees to perform repetitive, well-codified, and structured work (which AI now handles), whereas it intensifies employees' workload of handling unstructured, high-level problem-solving.

Is AI theoretically important to this design? AI is essential to this division of labor, hence, job design changes for two reasons. First, if the initial portion of the task is delegated to other employees, two problems emerge. The first problem pertains to the interdependence between the two tasks. AI performs repetitive, well-codified work with greater reliability and consistency than human workers, whose performance can be negatively affected by boredom and fatigue (Barbalet 1999, Casilli and Posada 2019). Therefore, employees handling the subsequent portion of the work may experience negative spillovers if

[2] In studying the division of labor between AI and humans in organizations, Jia et al. (2021) examined a parallel division of labor when AI and managers use their respective strengths to jointly produce feedback for employees in the process of creating complementarity greater than what each can generate independently.

the delegated portion is not performed consistently by other human employees. This negative experience or concern may undermine focal employees' perceived autonomy or personal responsibility for their work (Hackman et al., 1975), thus reducing their intrinsic motivation at work, including being creative (Zhou and Shalley, 2003). Increased task interdependence constrains employees and complicates their behavior at work (Chae and Choi, 2018).

The second problem is that this alternative design represents a regression of the established insights of the job enrichment model (Hackman et al., 1975; Hackman and Oldman, 1980), which advocates for making work more "interesting, challenging, and intrinsically motivating" (Elsbach and Hargdon, 2006, Page 470). These features are the opposite of the well-codified, repetitive work that AI can handle, so hypothetical employees to whom, instead of AI, this work is delegated will experience the known negative consequences that scholars of job design have strived to avoid.

Second, AI is the most advanced among existing technological tools for handling well-codified and repetitive work. For example, conversational AI is a mature technology widely adopted by many industries (Debecker 2019). Compared with alternative technologies, such as previous-generation rule-based pre-recorded systems, AI conversational bots are more powerful. This is because alternative technologies cannot engage in human-like conversations, resulting in less effective information exchange and a higher likelihood of triggering customer aversion (Luo et al. 2019).

Theoretical Tension Over AI-Augmented Employee Creativity

In organizational research, employee creativity refers to intentionally generating new and useful ideas, methods, or practices (for a comprehensive review, see Anderson et al. 2014).[3] Employee creativity is a context-based concept that refers to employees' generation of new ideas to solve problems in an organizational context. An employee's new idea to address a problem in the focal organization may resemble ideas already developed elsewhere. However, to the extent that the focal organization does not

[3] A closely related concept is innovation. Organizational scholars distinguish innovation as "both the production of creative ideas as the first stage and their implementation as the second stage" (Anderson et al. 2014, p. 1298). Further, it is important to distinguish creativity from novelty or radicalness—some new ideas are more radical or novel, whereas other new ideas are less novel and more incremental (Anderson et al. 2014; Zhou and George 2001).

know those existing ideas and thus faces a problem that would otherwise not be solved had the employee not generated the new idea, we consider this employee to have demonstrated creativity. Therefore, an employee does *not* have to be the first or only one in the world to generate ideas that are considered creative. Thus, employee creativity is a within-organizational phenomenon that varies at lower levels, such as individuals, teams, and tasks (Anderson et al. 2014).

Based on research on job characteristic models and employee creativity, there exists theoretical tension regarding whether the changes in job design induced by the sequential division of labor between AI and human employees increase employee creativity, thus generating AI-augmented employee creativity.

There are two reasons for this positive effect. First, the changed job design helps with the conservation of resources (Hobfoll, Shirom, and Golembiewski, 2000) needed by employees for higher-level problem-solving. When employees can use the output generated by the well-codified and repetitive work carried out by AI without having to conduct these activities themselves, they can invest their conserved cognitive, mental, and emotional resources to solve subsequent higher-level problems than when they have to handle the initial work themselves. With greater conservation of such resources, employees are more likely to stay focused on the work at hand, which increases the likelihood of achieving creative outcomes (Oldham & Cummings, 1996).

Second, the changed job design, by eliminating the well-codified and repetitive portions of tasks from employee responsibilities, increases the overall complexity and challenges of the problems that employees are exposed to at work. Research has found that, when facing complex and challenging jobs, employees become more motivated, proactive, excited, and entrepreneurial, which increases the number of new ideas they generate (Oldham & Cummings, 1996; Chae & Choi, 2018; Shalley, Gilson, & Blum, 2009). A critical mechanism is the sense of autonomy: employees report achieving more creative outcomes when they consider working on challenging assignments that offer them more freedom (Amabile and Grykiewicz, 1989; Hatcher et al., 1989). Another mechanism is that when employees are more excited about work, they have a higher intrinsic motivation to explore new paths and find new solutions, which critically increases their creativity (Amabile et al. 1990).

However, an opposite outcome may occur for two reasons. First, increased workload pressure constitutes an obstacle to employee creativity (Amabile, et al., 1996, Perlow, 2001; Elsbachand Hargadon, 2006). High job demands heighten workload pressure to overcome cognitive challenges and cope with time pressure, and lower job control over timing, pacing, and quality of work (Elsbach and Hargadon, 2006). For employees, the focal job design, while alleviating workload pressure from the repetitive, well-codified portion of the task, intensifies the workload pressure of solving higher-level problems. Solving higher-level problems is more cognitively challenging than performing well-codified work, and it does not always result in the luxury of greater control over the timing, pace, and quality of work. If the AI-induced change in job design *increases* the overall workload pressure, it threatens to reduce employee creativity.

Second, in addition to tangible resources provided by organizations that enable employees to search for new solutions (for a review, see Anderson et al. 2014), the perception of greater organizational support is more likely to increase employee motivation to search for newer and better solutions (Liu et al. 2017; Farmer, Tierney, Kung-McIntyre, 2003), thus increasing employee creativity (Zhou and George, 2001; Shalley, Gilson, and Blum, 2009). While employees may view organizations' use of AI in the sequential division of labor as aiding them in their jobs, hence increasing organizational support, there also exists a salient concern that AI adoption triggers employees' fear of job displacement by technology (Tong, Jia, Luo, and Fang, 2021), which can be perceived as lowered organizational support for employees.

Despite the competing implications for the effect of a sequential division of labor between AI and human employees on employee creativity, our core argument is that employees' job skills constitute a critical condition for delineating the competing effects, which we illustrate next.

Critical Condition of Job Skills: Skill-Biased AI-Augmented Employee Creativity

We consider employees' job skills to be a critical condition that delineates two competing implications for AI-augmented employee creativity. Employees' job skills are their domain expertise or knowledge of how to carry out the tasks required by their jobs. Job skills determine how well employees can overcome challenges encountered at work; thus, these abilities matter to how well they perform relevant tasks (MacInnis, Moorman, and Jaworski 1991).

Recall that the arguments for a positive effect produced by the changed job design as a result of a sequential division between AI and human employees on employee creativity include that it conserves the cognitive resources of employees and that it increases the complexity of the work handled by employees, both of which are conducive to employee creativity. These mechanisms are stronger for employees with higher job skills because they need to possess sufficient domain-relevant expertise to capture the opportunities to demonstrate the creativity presented to them by complex tasks (Liu et al. 2017) or conserved resources. That is, without a sufficient amount of domain knowledge needed to develop new solutions, employees will not be able to achieve creativity, no matter how motivated or energized they are to do so. Several existing theories have highlighted the importance of expertise in creating new ideas. The componential theory of employee creativity holds that domain-relevant skills are important drivers of employee creativity in that domain (Amabile, 1996). As supported by absorptive capacity theory (wherein greater existing knowledge enables individuals and organizations to learn new knowledge better; Cohen and Levinthal 1990) and the theory of innovation (wherein new knowledge results from the recombination of prior knowledge; Fleming et al. 2007), greater existing skills of employees in the job-related domain improve their ability to find new solutions to problems. Therefore, the greater an employee's job skills, the more likely they are to take advantage of the cognitive resources conserved, and the higher the job complexity generated by the AI-induced changes to the job design, both of which are conducive to workplace creativity.

Recall that countervailing arguments are rooted in concerns over the changed job design intensifying the workload pressure of employees or being perceived by employees as reduced organizational support owing to their fear of displacement by AI. While both concerns are obstacles to employee creativity, we argue that they are alleviated to a greater extent for employees with higher skills. First, although the changed job design increases employees' workload of engaging in high-level problem-solving, higher job skills enable employees to solve problems in their job domain, so the overall workload pressure is less likely to increase or increase to a lesser extent, for higher-skilled employees. Second, when employees have higher job skills, they develop greater advantages in a "horse race" with AI, which alleviates their concerns about being replaced by AI (Qin, Jia, Luo, and Liao, 2022).

Consequently, the positive impact of the changed job design resulting from a sequential division of labor between AI and human employees on employee creativity is amplified when employees with higher job skills are involved. In contrast, the potential negative impact is alleviated for higher-skilled employees. As a result, we conclude that the sequential division of labor between AI and human employees is more likely to increase the creativity of employees with greater job skills. In other words, AI-augmented employee creativity is more likely for employees with better job skills; hence, it is skill-biased. The following hypothesis supports this conclusion.

H1: *In an organizational task with a sequential division of labor between AI and human employees, AI assistance with handling the initial well-codified, repetitive portion of the task is more likely to increase employees' creativity in solving subsequent higher-level problems of the task when these employees have higher job skills.*

Figure 1 summarizes the chain of logic employed to generate this conclusion.

[INSERT FIGURE 1 HERE]

Performance Implications

By demonstrating greater creativity at work, employees generate new and useful solutions for problems whose answers have not been developed, which increases the likelihood of completing tasks and thus achieving better job performance (Gray, Knight, and Baer, 2020). It has been demonstrated that higher employee creativity is a critical path to increasing job performance (Anderson et al., 2014; Thomke and Fujimoto 2000; Zhou and George 2001; Chae and Choi, 2018). Therefore, if giving AI assistance to employees increases their creativity, then it follows that AI assistance ultimately increases employee job performance. Thus, we hypothesized that AI assistance could improve employee job performance by increasing creativity at work, as captured by the following hypothesis:[4]

H2: *If AI assistance with handling the initial well-codified, repetitive portion of the task indeed increases employees' creativity in solving subsequent higher-level problems of the task, then increased employee creativity is a path for AI assistance to increase employees' performance.*

STUDY 1: A FIELD EXPERIMENT

Field Experiment Setting

We conducted a randomized field experiment in a large telemarketing company in Asia, the name of which will remain confidential owing to company preferences. This company specializes in selling a wide variety of products and services to more than 30 million customers across multiple industries, including telecom, retail, fintech, and real estate. At the time of the experiment, the company was preparing to launch a new business line for marketing credit cards in partnership with a major bank. None of the employees had prior experience selling credit cards before the launch. Our experiment was conducted at the beginning of the new business launch after employees received basic training on selling credit cards with relevant scripts. This ensured that all employees had equal prior exposure and knowledge specific to credit card sales.

The company has adopted the common practice of designing sales tasks as two sequential components. In the first stage, employees call customers to introduce general information about the product and probe the initial interest of customers to generate "sales leads," described as customers who are interested in learning more about the product (without yet committing to make a purchase). Customers who were not interested were filtered out. The sales lead generation was a well-codified activity for which the company provided numerous protocols and scripts. The second stage pertained to sales persuasion, wherein employees continued serving the leads by finding out more about their needs, trying to match their needs with the product, and convincing the lead to make a purchase (i.e., to apply for a credit card in

[4] H2 does not hinge on distinguishing employees' job skills, because for the mediation hypothesis in H2 to hold, we only need to satisfy the condition that AI assistance indeed increases employee creativity.

our setting). Sales persuasion was considered a much less structured activity than sales lead generation. While the company provided training to employees with a knowledge bank, unexpected questions commonly occurred, and the knowledge bank needed to be updated.[5] However, these two stages were closely connected as a single sales task because the initial lead generation critically enhanced the effectiveness of subsequent second-stage sales persuasion by saving effort and mental power that would otherwise be wasted on trying to persuade customers who are inherently uninterested in the product (Sabnis et al. 2013).

The company used AI conversational bot technology to generate sales leads and reduce labor costs. The AI conversational bot was empowered by cutting-edge deep learning neural networks, voice recognition algorithms, and natural language understanding via bidirectional encoder representations from transformers (Brynjolfsson and McAfee 2014; Davenport, Guha, and Grewal 2021; Luo et al. 2021). It was trained with terabytes of telemarketing call data and could engage in natural, human-like conversations with customers. Its "speech-to-text" process recognized human language and converted audio data to a machine-understandable language. Moreover, "grammatical parts-of-speech tagging" identifies each word in the corpus based on its definition and context.

Furthermore, the AI conversational bot applied deep learning algorithms to dynamically understand the answers to customer questions based on both correct answers (positive samples), which increased the probability of sales and incorrect answers (negative samples). Via the "text-to-speech" function, the trained AI conversational bot could understand customer questions and communicate correct answers drawn from the knowledge bank to the customers in natural conversations. According to the company's records, the AI conversational bot passed the Turing test because, during the short (two–three minute) phone conversation, nearly 97% of the customers failed to distinguish the AI conversational bot from human agents. A high-tech firm developed and commercialized AI technology before licensing the focal company. [6]

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[5] Our semi-structured interviews in Study 2 provide more evidence of divergent features of work at the two stages.
[6] Similar to the AI conversational bot used here, many other AI conversational bots such as Cogito, Amelia, and

As the sales lead generation is well codified and highly scripted, the trained AI conversational bot can handle this work proficiently, for which we provide more evidence in the next section. However, current forms of AI technology are less effective in conducting sales persuasion, which is less codifiable and requires conversations that exceed the scope of scripts. This is because customers may have numerous idiosyncratic reasons for not applying for a credit card even after they are confirmed as leads (Raisch and Krakowski 2021). Owing to these common features of current AI conversational bots, industry experts have recognized that customer service jobs that involve a human following a script to interact with customers are at the greatest risk of being replaced by AI. Human interactions that require real, unscripted conversations are not at risk (McKendrick, 2021).[7]

Experimental Design

The task is to sell credit cards to customers through outbound sales calls. The field experiment followed a two (with AI assistance versus no AI assistance) by two (top versus bottom employees) full-factorial design, resulting in four experimental groups.

The first pertains to the presence of AI assistance. In the groups with AI assistance, the AI conversational bot made outbound calls (the identification of AI was not revealed to customers). If the customer indicated an interest in learning more about the credit cards (i.e., the customer was confirmed as a lead), the conversational bot would thank the customer and hand over the call to a human employee, who was referred to as "an exclusive VIP client manager," to serve as the lead in the sales presentation. An employee makes outbound calls in groups without AI assistance to generate sales leads. If the

Amazon Lex have been widely adopted across several industries, such as advertising, airlines, automobiles, banking, finance, healthcare, and retail (Luo et al. 2019; Gossett 2021). Over 80% of Fortune 500 companies use AI conversational bots in their call centers to save on labor cost and improve customer services (Insider Intelligence 2021).

[7] We also have one experimental group in which the AI conversational bot engaged in both lead generation and sales persuasion, without any human agents involved. Because of the absence of human involvement, insights developed from this treatment group do not directly help us address the research question of this paper which hinges on human agent's creativity demonstrated during sales persuasion. Nonetheless, we find that, compared with human employees conducting those activities, the AI conversational bot was as effective as human employees in generating sales leads (this result is consistent with those shown in this paper) but lagged behind top-skilled human employees in sales persuasion. More details are included in Appendix 11.

customer indicated an interest, the same employee would thank the customer and say they would become the "exclusive VIP client manager" to continue the call and engage in a sales presentation.

Human employees and an AI conversational bot follow the same protocols to generate sales leads. We restricted the AI conversational bot to following common protocols rather than allowing it to dynamically learn customer preferences and personalize the conversation with each customer (which is more difficult for human agents). This restriction likely makes our results more conservative. Furthermore, the partnering bank developed and provided common protocols and scripts used by employees and the AI conversational bot. Appendix 1 provides an example of the protocol used. A typical protocol includes several steps: opening, product introduction, elaboration, and ending/transfer. AI and human agents called all customers during the same period (1–3 pm on a Wednesday).

The second factor of the experimental design pertained to employees' expertise. We distinguish top employees from bottom employees based on their prior performance. Specifically, we ranked employees based on their sales volumes of other products for the previous months. We identified employees whose performance was in the lowest and highest terciles (i.e., the bottom 33% and top 33%, respectively) and then selected 20 employees from each tercile whose performance was closest to one another. Using this approach, we maximized the performance difference between top and bottom employees and minimized the performance variation within each group. The employee performance supports this group assignment demonstrated in a pretest in which we had these 40 employees sell another product (results are available upon request).

We randomly assigned 40 top and bottom employees to be assisted by AI or work independently and randomly assigned 3,144 customers to each of the four experimental groups.[8] Figure 2 illustrates the design of the treatment groups.

[INSERT FIGURE 2 HERE]

[8] Within each group, we also stratified the customer sample based on whether customers had previously inquired about the credit cards with the partnering bank (cold call versus warm call customers) for validity check, as illustrated later.

Data, Variables, and Randomization Checks

A customer-level dataset was constructed; customers constitute an important level of analysis because each customer essentially represents a "sales task" for employees to handle. We analyzed this dataset and focused on how well each sales task was performed. We captured two outcomes—creativity and performance–achieved by employees, who are called sales agents in this context, serving each customer during sales persuasion.

To measure an employee's creativity during sales persuasion (i.e., sales presentation to confirmed leads), we analyzed the audio data of all calls in our experiment. A dedicated AI algorithm first identified whether each question asked by customers during sales persuasion was within the scope of the knowledge bank that was used to train employees before the experiment. For questions that fell outside the scope of the knowledge bank (i.e., "untrained" questions"), an experienced manager determined whether employees successfully answered them.[9] Employee creativity is measured by *solving outside-knowledge-bank questions*, which is the ratio of *untrained* questions successfully *resolved* by the employee to all questions asked by the focal customer.[10] Thus, not all employees' answers to untrained customer questions are automatically counted as creative. Instead, answers were needed to solve the "new" question (i.e., questions that exceed the scope of the knowledge bank), thus becoming both novel and useful—two key criteria for determining employee creativity (Liu et al. 2017). Thus, our measure of employee creativity is objective and draws on "hard data" on employee behavior, extending the common approach of measuring

[9] Two pieces of critical information contribute to our confidence in the measure. To enhance their competitive advantage, the company considered it an important strategy to continuously identify untrained questions that emerged during the focal time window, create scripts for those questions, and use this information to expand their knowledge bank. The company undertook two actions. The first was to regularly use the aforementioned advanced AI algorithm to compare recorded sales calls with the existing knowledge bank, to identify untrained questions. This application is primarily enabled by ASR (automatic speech recognition) and NLP (Natural Language Processing), and the algorithms that support each reached over 98% accuracy. These algorithms have also been widely commercialized, including being adopted by the largest e-commerce platform of the country. Second, the company hosted regular meetings with multiple domain experts and experienced managers to assess how agents handled untrained questions and develop scripts for them. In the meeting that occurred after the experiment, the focal manager's judgements about whether each untrained question was successfully answered or not were all confirmed by this group of experts.

[10] We use the proportion to account for the workload of serving the given customer. We note that customers asked substantially fewer questions outside the scope of the knowledge bank than those within the scope.

employee creativity based on recalls and perceptions (e.g., Anderson et al. 2014; Liu et al. 2017; Zhou and George 2001).

Employee performance is captured by *customer purchase*, a binary variable indicating whether customers used the link sent to them to open a credit card within 24 hours after the sales call. Approximately 4% of all customers who received outbound calls ended up applying for credit cards; among the customers confirmed as sales leads, the purchase rate was 8%. Nearly half of the customers who received outbound calls were confirmed as sales leads.

Based on the four treatment groups, we constructed *AI-Human Hybrids*, which equals one for the two experimental groups that involve AI assistance to either type of employee and zero for the remaining two experimental groups that do not involve AI assistance. We construct *Top Agents*, which equals 1 for the two experimental groups that involve top employees with or without AI assistance, and 0 for the remaining two experimental groups that involve bottom employees with or without AI assistance.

We also collected information on customer demographics to provide more information on the sales tasks faced by employees. On average, customers receiving outbound calls in the experiment were 31 years old, and approximately half were men. They were relatively well educated, approximately 70% holding undergraduate or postgraduate degrees. Approximately 25% of customers owned at least one credit card before the call. We also surveyed sales leads on the extent to which they perceived being handed over for a sales presentation as a disturbance to address potential confounding effects. Panel A of Table 1 presents the summary statistics of all variables and pairwise correlations.

[INSERT TABLE 1 HERE]

Randomization checks were performed on the task heterogeneity (customer demographics) across the four experimental groups. Table 2 presents the results. Across all covariates, F- and chi-square tests indicated that the differences in the mean values across the experimental groups were jointly insignificant; thus, our data passed the randomization checks.

[INSERT TABLE 2 HERE]

Results on Employee Creativity

First, we present the model-free evidence. Figure 3 demonstrates the means and standard errors of *solving outside-knowledge-bank questions* for the two aggregate experimental groups that differed in terms of whether AI assistance was used for lead generation. With AI assistance, an average agent was 2.33 times as successful in answering questions they were not previously trained for and thus had to generate answers as their counterparts that did not have AI assistance. This difference was statistically significant ($p < 0.05$). These results indicate that the *overall* effect of AI assistance on the creativity of an *average* employee is positive. However, to test our hypothesis that employees' job skills constitute a critical condition, we differentiate treatment groups based on whether they involve top or bottom agents. Figure 4 shows the means and standard errors of *solving outside-knowledge-bank questions* for all four experimental groups. Although AI assistance helps both agents at the top and bottom to demonstrate greater creativity than without AI, the magnitude of this increase is much more pronounced among top agents than among bottom agents ($p < 0.01$). Specifically, for top agents, the magnitude of the increased success in answering untrained questions due to receiving AI assistance, compared with no AI assistance, was 2.81 times that of bottom agents. Thus, these results support H1.

[INSERT FIGURES 3 AND 4 HERE]

We also validated these findings using regression results. We regress *solving outside-knowledge-bank questions* on indicators of *AI-Human hybrids*, *top agents*, their interaction term, and all control variables, with standard errors clustered at the agent level. Table 3 presents the results. Model 1 in Table 3 contains all control variables. Model 2 in Table 2 adds *AI-Human Hybrids* as a covariate. This shows that all else being equal, an average agent with AI assistance demonstrates greater creativity in *solving outside-knowledge-bank questions* than the average agent without AI assistance by a degree that amounts to 10% of the mean value of *solving outside-knowledge-bank questions*. This is a substantial increase.

Model 4 in Table 3 shows a positive interaction effect produced by *AI-Human hybrids* and *top agents*. This indicates that the enhanced creativity demonstrated by agents as a result of AI assistance in lead generation is even more pronounced for highly skilled agents than for bottom agents with lower job skills. As an alternative way to demonstrate the moderating effect of an agent's job skills, Models 6 and 7 in Table 3 examine the main effect of *AI-Human Hybrids* on employee creativity in the subsamples of top and bottom agents, respectively. While agents with AI assistance demonstrate greater creativity than those without such assistance in both subsamples, the magnitude of the estimated effect of AI assistance among top agents is six times that of the bottom agents, further substantiating H1. To address the concern that agent-level variation (top vs. bottom agents) moderates the effect of task-level variation (customers served by AI-human teams versus humans on their own) on task outcomes (customers' questions answered), we also employ multilevel models, which generate consistent results, as reported in Appendix 2.

[INSERT TABLE 3 HERE]

Alternative Explanations. As a result of our experimental design involving a two-stage sequential labor division, we checked whether a selection bias existed in the first-stage sales lead generation, which may confound second-stage sales persuasion outcomes, including employee creativity and performance, which we will discuss next. Therefore, we examine the effect of AI assistance on the likelihood of generating sales leads in the first stage. As Appendix 3 shows, all four treatment groups performed similarly in generating sales leads. This finding also confirms the key assumption we made in the theory development that first-stage sales generation is repetitive, well-defined, and scripted work that does not leverage much sales capability. Thus, employees with lower expertise levels perform as well as those with higher expertise levels, and AI performs as proficiently as human employees. The results confirmed that no selection occurred during the first-stage lead generation.

Furthermore, sales leads confirmed in the first stage by different experimental groups were homogenous. We examined the demographic characteristics of sales leads generated by the four experimental groups. Appendix 4 shows that the one-way analysis of variance (ANOVA) and chi-square test fail to reject the null hypothesis that the mean values of these variables for sales leads are *not* different among the four experimental conditions. These results further alleviate concerns that the heterogeneity of sales leads might confound the results that performance and employee creativity demonstrated in persuading sales leads to make a purchase vary across the treatment groups.

Finally, a necessary condition for successfully addressing outside-knowledge-bank questions is that such questions must be asked by customers to agents first. Therefore, we examined whether there was a systematic difference in the availability of such questions between the treatment groups. Appendix 5 shows that, among the four treatment groups, customers asked a similar number of questions outside the scope of the knowledge bank. Thus, we can alleviate the concern that heterogeneous questions asked by consumers drive findings on employing creativity.

Validity Check. If the theory that AI assistance enables employees to demonstrate a higher level of creativity holds true, this causal relationship should manifest more strongly in situations that create greater opportunities to demonstrate creativity. Specifically, when serving customers who ask more outside-knowledge-bank questions, the theorized relationship should be more pronounced than when serving customers who ask fewer questions. This is because, in the latter case, there is less need to create answers to outside-knowledge bank questions.

Customer heterogeneity creates the opportunity to conduct a validity check. Some customers had inquired about the credit cards with the bank before the bank entered a partnership with the focal telemarketing firm to sell the credit cards, which we call 'warm call' customers. Otherwise, they are referred to as 'cold call' customers. Customers who inquired about this product may have a greater need for it; thus, they could be more easily persuaded by agents to purchase during the sales persuasion stage (Alwitt and Pitts 1996; Tauber 1973). Indeed, Appendix 6 shows that the average "warm call" customer is almost twice as likely to make a purchase than an average "cold call" customer. One may speculate that customers who had inquired about credit cards might have possessed more knowledge and thus might demand more sophisticated services before making purchase decisions, making them more difficult to sell. However, this speculation is not consistent with our data. Appendix 7 shows that the outside-knowledge-bank questions asked by "cold call" customers are more than four times that asked by "warm call" customers. To summarize, "cold call" customers asked more outside-knowledge-bank questions and were less likely to make purchases than "warm call" customers.

We used stratified sampling to ensure that each treatment group served approximately the same number of customers of each type. Figure 5 presents *solving outside-knowledge-bank questions* for eight groups, with each of the four treatment groups further divided into "cold call" and "warm call" customers. The results show that both the positive effect of AI assistance on solving questions outside the knowledge bank and the enhanced moderating effect of top agents are present among "cold call" customers (who ask more questions outside the knowledge bank), as indicated by the gray shades. However, these effects are nearly absent among "warm call" customers (who ask a few questions outside the knowledge bank). Thus, these results validated H1.

[INSERT FIGURE 5 HERE]

Results on Employee Performance

H2 posits that providing AI assistance to employees improves their performance by increasing their creativity to solve problems at work, particularly when higher-skilled employees are involved. First, we compared the customer purchase rates for the experimental groups with and without AI assistance, as shown in Figure 6. We find that customers served by an AI-assisted sales agent are almost twice as likely to make a purchase than those served by sales agents alone, and this difference is statistically significantly different from 0 ($p < 0.05$).

[INSERT FIGURE 6 HERE]

However, the unconditional mean comparison does not directly test H3. We conducted a causal mediation analysis for randomized experimental data (Imai, Keele, and Tingley, 2010) with 1,000 bootstrap replications (Preacher and Hayes 2004). We use *Customer Purchase* as the dependent variable, *AI-Human Hybrids* as the independent variable, *Solving Outside-knowledge-bank Questions* as the mediator, and all control variables. We report the regression results in Appendix 8 and summarize the key estimates in Figure 7. The results show that agents with AI assistance, compared to those without, are more successful in solving outside-knowledge-bank questions (which confirms the results mentioned above). In turn, this enhanced success further increases customer purchases. These results support H3.

[INSERT FIGURE 7 HERE]

STUDY 2: SEMI-STRUCTURED INTERVIEWS

Motivation of Mixed Methods

Mixed-methods approaches provide "triangulation" to improve the confidence that results are not produced by some artifacts of a particular data source or method (Jick, 1979) and generate opportunities to enrich explanations (Creswell and Creswell, 2017). In our study, both studies had distinct strengths and weaknesses. The field experiment provides causal identification of objective outcomes based on actual workplace behavior when real economic interests are at stake (Harrison and List, 2004), but it does not directly reveal the mechanisms. Semi-structured interviews do not produce causal relationships and are subjective but enrich our knowledge of the behavioral and psychological processes that constitute mechanisms. Using these two methods contributes to and compensates for the weaknesses of each method (Siebel, 1973; Small, 2011), thus creating complementarity (Small, 2011). We used a field experiment as the primary study to establish causal evidence, followed by an inductive, qualitative study to enrich our understanding of the mechanisms.

Data and Analysis Strategy

To further unpack the theoretical mechanisms through which AI assistance shapes employee behavior and performance at work, we conducted 28 semi-structured interviews with a random sample of sales agents who participated in the experiment, stratified between agents who received AI assistance and those who did not, and between the top and bottom agents (i.e., we had the same number of interviewees from each of the four treatment groups). This nested design enables researchers to penetrate deeper into the subjects of study (Small, 2011).

All interviews were conducted in person and lasted between 50 and 90 minutes. Although we used an interview protocol as a guide (Appendix 9), we encouraged interviewees to talk freely about their experiences, share stories and examples, and express their feelings and emotions so that they could discuss what they considered relevant and important (Weiss 1994).

Subsequently, we followed a grounded theory approach to engage in inductive data analysis, which comprises three stages (Strauss and Corbin 1994). In the first stage, we conducted open coding to generate common themes as first-order codes and assigned tentative categories. For example, first-order codes capture highly skilled agents expressing happier and more relaxed feelings from serving the sales leads generated by AI. As the data analysis progressed, some tentative categories were later preserved, whereas others that did not fit the data well were revised or abandoned. In the second stage, we consolidated first-order codes into second-order theoretical categories and focused on the contrasts and connections among the categories (Gioia, Corley, and Hamilton, 2013). For example, interviewees' descriptions of the positive feelings they experienced from serving the sales leads generated by AI, including better mood, high morale, and a sense of freedom, pointed to a common theme of positive emotions experienced while performing specific tasks. Descriptions offered by interviewees on the pride and honor they felt about their firm's adoption of AI, the feelings of greater recognition of their work, and greater organizational support pointed to related (in terms of psychological factors) but different categories of enhanced organizational commitment that are not task specific. We generated additional aggregated theoretical dimensions in the third stage based on second-order categories. Thus, we drew on previous research that distinguished cognitive skills from psychological factors as distinct determinants of employee performance (e.g., Duckworth, Quirck, Gallop, and Matthews 2019). Figure 8 summarizes the data analysis process and the resulting framework of analysis, which we will elaborate on next.

[INSERT FIGURE 8 HERE]

Finding 1: AI Assistance Alters Job Design for Employees

All agents pointed to the design of having AI make outbound calls to customers to probe initial interest (lead generation) and pass confirmed leads only to human agents for a sales presentation as creating critical change to their work mode. First, the nature of lead generation was considered by agents to be "hard labor…[because] if you reach out to customers by yourself, there will be many situations including connection failures, customers hanging up on you, and customers scolding you upon picking up the calls" (#H5)[11] and "you rarely have real communication with customers" (#H1). Thus, multiple

[11] The letter and numbers in parentheses identified the interviewees who provided the quote. Letter "H" indicates an interviewee from the highly skilled agent sample, and "L" indicates an interviewee from the lower-skilled agent

interviewees described the lead generation as being boring, “requiring no skills” (#L1), and “highly-frequent but minimally-effective communication” (#H13).

Second, with AI assistance screening out customers who had minimal intention to purchase, a significantly larger proportion of customers who were passed to agents “had clear ideas about what they want” (#H9), “were truly willing to listen to [agents’] introduction [of the product]” (#H6), and thus of “high value” (#H13). Another change was that agents’ “likelihood of actually engaging in conversations with customers was almost 100%” (#L3). However, without AI screening, such conversations were “seldom” (#L5) because agents spent most of their time “trying to get connected, [dealing with] hang-ups, and having very short conversations if customers even picked up the calls” (#L13). These changes have “increased the intensity and challenges of [agents’] work” (#L14). Therefore, these findings corroborate the initial stage of our theoretical framework, in which AI changes job design.

Thus, these findings corroborate the arguments we provided as the first step of the theoretical framework that a sequential division between AI and human employees changes job design by alleviating employees’ burden of handling well-codified, standard work but intensifying the need for employees to solve more complex, higher-level problems.

Overall divergence. It is interesting to note that highly skilled and lower-skilled agents reported a drastically different impact produced by this change on their work performance and psychological well-being in general. Although highly skilled agents also recognized that with AI assistance, “the difficulty of the content of [their] work has increased” (#H7), they considered it “a good thing for [their] efficiency and performance” (#H7) and commonly reported feeling “elated…because this changed work mode significantly helps and improves [their] work” (#H13). Specifically, they both expressed relief about not having to generate sales leads and considered that more intensive interactions with sales leads offered greater career opportunities.

> *“After all, for us, dealing with those boring, non-technical things [lead generation] every day is a bit overkill. We should be assigned to a more difficult business.”* (#H12)

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sample.

"I have no problem dealing with questions that I have been trained on, but I think we need to have more opportunities to contact customers. Only after communicating with customers can I know what problems exist, how to deal with those problems, and then think about it repeatedly to further improve my scripts, invent new scripts, and better deal with these problems when I encounter them again in the future." (#H11)

Conversely, lower-skilled agents considered this change to have lowered their speed and efficiency at work because AI assistance increased the likelihood that they encountered customers who were serious about the products and, thus, were more challenging to serve. However, owing to their limited abilities, they experienced many difficulties in persuading customers to move forward with a purchase.

"[AI assistance] only reduces our work efficiency because AI has processed all the simple and unskilled tasks, and all the subsequent cases require a certain level of skills in [using the right] scripts, so we will naturally be much slower to process the cases. The duration of serving each customer increases, and the number of customers we can serve is significantly reduced." (#L2)

Moreover, lower-skilled agents described the increased pressure they felt from serving a larger number of challenging customers, as the following quotes vividly demonstrate.

"Although the frequency of communication with customers increases, the difficulty of customers' questions raised during the communication process also increases. I am more likely to become stuck without knowing how to answer the questions raised by customers. It may make customers feel that I am less professional; thus, for me, the sense of pressure is multiplied, and I must learn as soon as possible to catch up." (#L10)

"It's like putting a doctor who only sees outpatients in the ICU to care for patients. There is a feeling of driving the duck on a perch. [In the local language, this is a proverb meaning to force someone to do something beyond their capability.] First and foremost, I do not have strong skills, and I easily become nervous when I encounter difficult clients. When I become nervous, I do not know what to do next. So, I am a little worried about failing to serve potential customers well." (#L7)

Although these findings are consistent with our theory of job skills as a differentiating factor, we will be able to provide a deeper analysis to delineate several mechanisms to explain why such divergence occurred, as illustrated next.

Finding 2: AI Assisted with Development of Cognitive Skills Conducive to Creativity

We find that key changes to the mode of work induced by AI assistance, on the one hand, affected the actual outcomes agents achieved in developing new scripts and improving existing scripts, both of which were considered "innovations" in this work context, albeit with a sharp divergence between highly skilled and lower-skilled agents. On the other hand, higher- and lower-skilled agents agreed that changes to their work mode should enhance their abilities to demonstrate greater creativity in the longer term. Each point is illustrated below.

Divergence between high- and low-skilled employees. AI assistance increases agent exposure to customers with a confirmed interest in the product. With this change, highly skilled employees reported developing enhanced job skills, which enabled them to generate new and improved answers to customer questions through two primary channels (denoted as [1] in Figure 8). In the first channel, highly skilled agents thought that by spending less time and effort on generating sales leads, AI assistance enabled them to "devote more time and stay more concentrated on thinking about how to resolve questions [that were challenging]" (#H9). Thus, they both developed new scripts for challenging questions as a pre-existing script was not available and improved existing scripts to make them more effective, both of which they called "innovations":

> *"AI assistance freed up more time for us to think more about how to overcome some difficulties. For example, when there was no AI assistance, about half of our day was spent dialing numbers and dealing with no answers, hang-ups, short conversations, and so on. Thus, we could not handle many real cases in one day. However, after AI intervenes, we can also handle the same number of cases in one day as we previously did but have a lot more time to think.*" (#H6)

> *"When I have sufficient time, I can think more comprehensively, and the answers to the questions are better… when I can concentrate better, my thinking will be more focused, and my answers to some on-the-spot questions should be more accurate."* (#H1)

> *"With the assistance of AI, we are liberated from tedious and repetitive calls to better focus on serving willing customers. We have more time and freedom to improve our skills and innovate our scripts continuously."* (#H3)

In the second channel, highly skilled employees discussed how more challenging cases called for newer and better answers from customers. Therefore, their increased exposure to these types of cases provided greater opportunities for them to develop new and improved scripts.

> *"There is a saying that 'knowledge comes from practice.' By constantly encountering problems in real businesses, solving them, and accumulating experience from serving challenging customers, we can continuously improve and innovate the content of scripts. Without AI assistance, we will not have that much time to interact with these valuable customers to update our answers to questions."* (#H9)

> *"[AI assistance] stimulates my creativity because I now more frequently encounter important and difficult problems. For the problems that we have been trained for, I can provide different solutions, continue to innovate them, and replace existing solutions with better ones."* (#H5)

We also collected several specific examples provided by highly skilled agents on new scripts they developed for untrained questions and better scripts to improve upon existing ones for trained questions.

Conversely, there was a major divergence in lower-skilled agents. Although lower-skilled agents also agreed that they saved time and energy and had increased opportunities to interact with customers from AI assistance, they felt that these changes did not make a difference in helping them find new or better answers because of their limited abilities and thus reported limited innovative outcomes (denoted as [2] in Figure 8).

> *"Paying more attention and spending more time [on solving questions] probably do not make a difference; I can't think of a better solution."* (#L5)

> *"Even with more time, I am not sure if I can find a better solution because solving some problems does not necessarily hinge on spending more time to think but on my limited abilities."* (#L6)

> *"I have low ability and a weak foundation, and it is difficult for me to innovate when encountering challenging cases."* (#L1)

Nevertheless, lower-skilled agents observed their highly skilled colleagues to solve challenging questions by developing new innovative answers:

> *"[I benefit from] the scripts developed by higher-performing colleagues. As AI manages cases that do not require skills, the remaining cases passed to humans are relatively more difficult. It is difficult for us to innovate for these cases, but my higher-performing colleagues can continue to break through and innovate, and it will also benefit us."* (#L14)

> *"In fact, [AI assistance] can indeed help us to explore see if we can innovate the answers to the problems for which we have been trained. Although I cannot do that myself, I have seen some outstanding colleagues coming up with new answers."*

These findings show that job skills or domain knowledge are important to creativity (Simon, 1985) because "creativity requires a complex thought process" (Shalley et al. 2009, Page 492). Moreover, these findings directly support our theoretical argument that without the necessary domain knowledge or job skills, conserved cognitive resources, and strengthened motivations alone cannot generate new ideas.

Convergence among employees. Beyond generating innovative solutions to specific cases that had occurred, agents discussed how this change generated by AI assistance could help them expand their general experiences and skills germane to developing better and newer solutions in the future. Both highly skilled and lower-skilled agents converge on how these general future benefits can be created by AI assistance. These general benefits fall into the following four categories.

The first category (denoted as [3] in Figure 8) is that increased interactions with customers can enable agents to collect customer feedback and reaction to the answers provided by agents, based on which agents can further adjust, adapt, and revise their answers: *"The more we contact customers who are willing to communicate, the greater the amount of information we obtain from them, and the more we can review and innovate our business through iterations"* (#H2). Greater awareness and willingness to respond to customers' reactions increases the likelihood that agents generate solutions that are more appropriate for the context than existing answers, which can lead to the innovation of new scripts.

The second category (denoted as [4] in Figure 8) pertains to agents' increased ability to distinguish opportunities to innovate scripts and to understand additional ways of improving current scripts. For example, *"we can accumulate more experience of serving complicated cases, which provides ideas for how to innovate in the future: the more customers we serve, the more we can judge whether there may be room to adjust the existing, trained way of solving problems"* (#L14).

The third category (denoted as [5] in Figure 8) pertains to an increased ability to handle cases with greater flexibility following the idiosyncrasies of the situation instead of sticking to pre-determined, trained solutions: *"After all, I have gained more practical experience and thus can handle problems more flexibly"* (#H5). A greater willingness to adapt to a situation enables agents to deviate from existing scripts, thus increasing the likelihood that they will generate better and newer solutions.

The last category (denoted as [6] in Figure 8) pertains to how increased exposure to real customers, because of AI assistance, enables the agents to stay calm and prepare to "play on the spot" in response to unexpected situations. For example, *"[t]he key to dealing with problems on the spot is to have enough actual 'combat experience' so that we do not panic, and we can readily use our skills to 'get the man.' Therefore, to deal with these problems well, we need to accumulate rich experience"* (#L2). As deviations from trained situations offer opportunities for new scripts or to improve existing scripts, better mental and cognitive preparation to "play on the spot" in such situations should increase the likelihood of generating newer and better scripts.

Thus, employees agree that four abilities are enabled by AI assistance: to use feedback from the customer to create innovative scripts; to identify opportunities to innovate scripts; to interact with clients more flexibly, thus calling for innovations with scripts, and to "play on the spot" to generate innovative scripts. All these functions are enabled by resources freed by AI assistance, thus enriching the process through which job design and conservation of resources change creativity (Chae and Choi 2018; Elsbach and Hargadon 2016; Shalley et al., 2009).

Finding 3: AI Assisted with Development of Psychological Outcomes Conducive to Creativity.

We found that the changed mode of work and its source of AI assistance produced various psychological consequences that may affect agent creativity. On the one hand, highly skilled agents experienced more positive emotions from performing the changed tasks, including better mood, increased morale, and greater passion. However, lower-skilled agents reported negative emotions, including nervousness, demoralization, and feelings of rejection. Better mood is important for the performance of service agents (Rothbard and Wilk, 2011). Positive emotions lead to greater creativity according to the broaden-and-build theory (Fredrickson, 2004). On the other hand, highly skilled and lower-skilled agents reported more positive sentiments about the firm's adoption of AI assistance and greater organizational commitment. In the following paragraphs, we elaborate on each of these categories.

Divergence between high- and low-skilled employees Diverging emotions associated with performing tasks at work include the following. First, with the changed work mode, highly skilled agents expressed three positive psychological outcomes while performing their tasks, whereas lower-skilled agents expressed the opposite (denoted as [7] in Figure 8). The first positive psychological outcome is "a greater sense of relief" and "a better mood" (#H6) for highly skilled agents, primarily for two reasons. The first reason was that they no longer needed to conduct "repetitive, tedious, and meaningless" (#H5) phone calls for lead generation, which they found "frustrating" (#H7): *"The work in the previous stage is always hard labor. If processed by humans, emotional fluctuations are inevitably generated. …it is a waste of my time and energy"* (#H5). Second, they felt more relaxed and happier engaging with clients willing to purchase.

> *"[With AI assistance,] all the customers whom I handle have intentions [to buy] and are willing to listen to my introduction. When chatting with them, I feel much more relaxed, and I am in a much better mood; thus, naturally, I feel that pressure at work is much reduced, and I feel greater relief and pleasure."* (#H6)

In stark contrast, dealing with such clients increased the pressure felt by lower-skilled agents who reported feelings of "depression and distress" (#L1):

> *"I don't feel relieved. However, it makes life more stressful because I have to deal with many more complex businesses. They give me headaches throughout the day; how can I be more relaxed?"* (#L9)

Second, as AI assistance exposed agents to the more challenging tasks of a sales presentation and persuasion, highly skilled agents commonly described a boosted "moral of combat" or "fighting spirit" (e.g., #H5, #H13). This resulted from being given additional opportunities to handle more important and challenging businesses and greater success in overcoming these challenges by having productive communication with customers that resulted in purchases (denoted as [8] in Figure 8). For example,

> *"This approach [using AI assistance] makes me feel that our work is quite challenging. After adopting AI assistance, we focus on dealing with more difficult problems, but the more challenging the customers are, the more motivated we are, and the more work we want to do."* (#H3)

The opposite effect was observed for lower-skilled agents. They first discussed how lowered efficiency and reduced speed of serving more challenging customers "interfered with [their] mentality at work, making it more difficult for [them] to do business in the future" (#L11). They also described how experiencing a larger number of occurrences in which they failed to persuade challenging customers reduced morale:

> *"Judging from my current performance, the customers who have passed the AI screening are a big challenge for me, and I am not always able to 'overcome' them. Thus, it is difficult to stimulate my fighting spirit. Conversely, it can make me lose confidence in my work."* (#L14)

> *"In addition to amping up pressure, [a change of work mode] gradually destroys my fighting spirit because the difficulty of the cases is too great, my progress is too slow, and the outcomes are not desirable. Thus, the work becomes increasingly less engaging."* (#L2)

Third, highly skilled agents described increased "work motivation" (#H9) and greater "passion" (#H6) from serving customers with real intentions to purchase during sales presentations than reaching out to random customers to generate sales leads. Interestingly, they also discussed how the changed mode of work gave them a greater sense of freedom to innovate.

> *"We have more opportunities to encounter difficult and challenging questions from customers, some of which are not in the knowledge bank; without the restrictions of the knowledge bank, we have more freedom to be innovative [with new scripts]."* (#H2)

Conversely, lower-skilled agents discussed being demoralized, as previously reported. Instead of feeling that dealing with new questions gave them the freedom to be innovative, they wished that "[i]t would be best if there was a standard answer to every question encountered' (#L9). (This contrast is denoted as [9] in Figure 8.)

Thus far, we have found a divergence between high-skilled and lower-skilled employees in terms of mood, morale, and passion resulting from receiving AI assistance. Positive emotions contribute to desirable outcomes at work, including employee creativity (Fredrickson, 2004). Therefore, such divergence can explain the diverging effects produced by AI assistance in achieving creative outcomes between the two groups because psychological states and emotions not only affect the sales process (Sutton and Rafaeli, 1988) but also critically shape employees' creativity at work (Elsbach and Hargadon, 2006; Knight, 2015; Zhang and Bartol, 2010).

Convergence among employees. Highly skilled and lower-skilled agents converged to express positive sentiments about the firm adopting AI to assist agents. The first sentiment is "a sense of pride" and "a sense of honor" (e.g., #L3, #L14, #H6, #H13) to work for a firm that adopts the latest AI technologies, as the agents considered such adoption to be "trendy" and a demonstration of "strategic vision" for the firm (#L11) (denoted as [10] in Figure 8). One agent elaborates as follows:

> *"[AI assistance] makes me feel more superior because AI is a big trend now, and the company is constantly innovating. Working in such a company makes me feel like I am at the frontier of our time, being fashionable and not rustic, just like buying the latest mobile phone models. My sense of pride naturally arises. Although other companies, such as Railway Construction Corporation and Sanitation Company, are large in scale and have state-owned enterprise backgrounds, they sound like yokels. I can even show off to my friends. I feel enthusiastic about working in such a work environment."* (#H9)

Second, all agents, regardless of their skills to persuade challenging customers, felt that increased opportunities for them to serve challenging customers demonstrated the firm's "recognition of [their] job skills" (#H33) and that the firm considered them to be "an indispensable part of the business" (#H33). Even lower-skilled agents who complained about their lack of ability to handle challenging customers thought that using AI assistance meant that "[t]he company still thinks highly of [their] work skills" so that they felt "proud to be assigned such complex and difficult cases" (#L4). (This point is denoted as [11] in Figure 8.)

Third, the agents considered the adoption of AI assistance to indicate that the company was willing to provide stronger technical support to better prepare agents for their communication with customers (denoted as [12] in Figure 8). For example, one explained that by adopting AI, the company "certainly gave us more support in business and laid the foundation for us to communicate with customers. At least the purpose of our communication does not need to be explained [to customers], so customers may become more likely to cooperate with us" (#L2). Moreover, some agents interpreted a firm's intention to adopt AI as providing employees with greater organizational support.[12]

> *"I think [by adopting AI] our firm wants us to have more opportunities to meet and communicate with real customers, so we don't have to repeat those high-frequency scripts."* (#L10)

Finally, it is interesting that all agents recognized the threat of being replaced by AI in the future, but they did not blame the company for it. While highly skilled agents described mixed feelings of appreciating the help they received from AI and were concerned about being replaced by AI in the future, they explicitly said that the company adopted the right strategy (denoted as [13] in Figure 8). For example,

> *"In the short term, [AI assistance] is a good thing, but in the long run, there will be threats. Although AI assistance with our work has helped improve work efficiency and capabilities, will it replace us when AI becomes even more mature in the future? Everyone understands this possibility, but current AI technology has been widely used, and it is correct for the company to adopt AI; otherwise, the company itself may be eliminated. Even if this stage [AI displacing agents] is reached in the future, it will be a necessary decision by the company for technological progress. If there are opportunities, we can choose to transfer them to different positions."* (#H13)

[12] While we have developed theoretical reasons why deploying AI assistance is more likely to be seen by higher-skilled employees as the firm rendering stronger organizational support to them than lower-skilled employees because of greater job displacement concerns of the latter, in the interview data we do not observe top and bottom agents expressing different views on organizational support. This outcome may be explained by the subsequent findings that while bottom agents are concerned about job displacement, they blamed the technology more than the firm for this risk.

Even lower-skilled agents considered the company's adoption of AI "an inevitable trend" (#L4) that was imperative for "the company's own survival" (#L1); thus, "the company's thinking is reasonable: the company needs to grow in the long run, the employees need to continuously make progress, and the new technologies need to continuously expand" (#L9). Lower-skilled agents called for more training and sharing experiences with highly skilled colleagues to help them adapt.

Against the backdrop of the common age of labor against technologies and firm owners (as demonstrated by famous historical events such as the Luddite and Captain Swing riots; for example, Mokyr, Vickers, and Ziebarth [2015]), we discovered that in this particular context of AI adoption by the focal telemarketing firm, employees appear to be understanding and supportive of technology adoption by their employers, which is interesting.

Finding 4: Performance Consequences and Suggested Changes to AI Adoption

Highly skilled agents commonly state that AI assistance increases their ability to meet key performance indicators (KPI). One agent compared their work post- and pre-AI adoption as "high efficiency and high quality versus low efficiency and low quality" (#H13). While lower-skilled agents generally complained about their lower likelihood of successfully persuading sales leads to purchase, some acknowledged that the net impact on their performance might not necessarily be negative: "In the past, the volume of business was large, and the success rate was low. Now, although the volume of business [that I can handle] reduced less, the success rate can be much higher" (#L1).

Consistently, most highly skilled agents advocated expanding the use of AI to handle more "ineffective calls that otherwise occupied too much of our time" (#H2). They also advocated using their innovations in scripts to actively update AI's knowledge bank:

> *"[AI involvement] can be maintained [at the current level] for now and gradually increased. As some of the difficult problems that we have encountered are not in the AI knowledge bank, [the company] needs us to continue summarizing our experiences and iteratively update the knowledge in the AI library"* (#H11).

Many lower-skilled agents advocated for maintaining the current level of AI assistance without expanding it: "if it continues to increase, the jobs that are left for us to handle will become even more difficult, and I am not sure if I can complete them" (#L3). Some lower-skilled agents acknowledged the tension between the company's interests and their own.

> *"From the company's perspective, [the use of AI assistance] should increase. As previously mentioned, this is a trend. From my personal perspective, it is good to maintain [my current level]. After all, those of us with poor performance need to be left with some work to do."* (#L10)

Employees' perceptions of their changed performance are consistent with our analytical results of their sales performance, although the latter may be seen as more objective and accurate. Their suggestions on whether AI adoption should be expanded are consistent with their positive and negative experiences.

Delegating AI's Task to Human Workers? We have provided a theoretical discussion on whether sales generation can be delegated to lower-cost human employees to produce the same results. We previously argued that, unlike humans, AI does not suffer from a potential decline in productivity because of boredom and fatigue when performing lead generation, a standardized, scripted, and repetitive work, so it is less likely to generate negative spillovers to human employees handling subsequent sales persuasion. The interview data corroborated this point. When asked about a hypothetical case of sales lead generation being taken over by other human employees instead of AI, agents expressed concerns about such negative spillovers from lead generation to sales presentations. They did not trust human employees to be as consistent as AI in handling the lead generation in compliance with instructions and training. They expected to expend more resources to fix customer relations if other human employees mishandled customers during the lead generation. As one agent expressed, "*Humans have emotions, especially when working on high-frequency and boring tasks, and are prone to developing unpleasant tones. Once the front-end [agents who generate sales leads] leaves a customer with a bad impression, it will be difficult for us to communicate with the customer afterward. The customer will trust us less, and we may even lose this customer*" (#L1). Therefore, it is theoretically important to involve AI in handling codified and repetitive activities to boost employees' creativity in subsequent higher-level problem-solving.

Summary

Semi-structured interviews corroborated our theory and contributed even richer, deeper, and more nuanced insights. First, the addition of AI assistance resulted in significant changes in the mode of work of human agents. Human agents no longer handle lead generation, which is well-scripted, repetitive, and mostly involves customers with a minimal willingness to communicate. They are more frequently exposed to serious customers who are interested but can ask tough questions.

Second, consistent with our theory, this model change saves agents time and energy, enabling highly skilled agents to generate new answers to untrained questions and/or improve existing answers to trained questions, thus demonstrating greater creativity at work. However, lower-skilled agents cannot do so. Beyond our theory, this change also increased agents' ability to (a) use feedback from clients to create innovative scripts, (b) identify opportunities to innovate scripts, (c) deal with clients more flexibly, which calls for innovations with scripts, and (d) "play on the spot" to generate innovative scripts. Thus, AI assistance generates positive cognitive outcomes (job skills) conducive to workplace innovation and more so for highly skilled agents.

Finally, beyond our theory, this change in work mode results in a better mood, increased morale, and greater passion for highly skilled agents, all of which are conducive to workplace creativity. Conversely, opposite changes occurred for lower-skilled agents, including greater pressure and lower morale. As our theory predicted, all agents expressed greater perceived support for the organization, but with greater nuances beyond our theory, including pride and sense of honor, perceived good intention of the firm, and avoidance of blaming the firm for potential future job displacement by AI. Thus, AI assistance also generates positive psychological outcomes conducive to workplace innovation and even more so for highly skilled agents. All the quotes are summarized in Appendix 10. These insights further enriches the mechanisms of the theoretical framework as indicated in Figure 1.

DISCUSSION

This study examines the organizational design of using AI in a sequential division of labor by assigning the repetitive, well-codified portion of a task to AI to generate the input needed to perform the portion of the task that requires higher-level problem-solving by human employees. Drawing on multiple theories, including AI-human collaboration, job characteristic model, and employee creativity, and mixed methods, we analyze whether AI assistance enables employees to solve higher-order problems more creatively, thus generating AI-augmented employee creativity. Results from a field experiment conducted in a telemarketing company provide causal evidence that such AI-augmented creativity is *skilled biased:* particularly for agents with higher job skills. During lead generation, AI assistance enhanced agents' success in developing new answers to customers' questions that exceeded the scope of the company's knowledge bank, thus demonstrating greater creativity than independently achieved by these agents. Findings from semi-structured interviews with agents revealed more nuanced insights into multiple channels through which AI enhanced the creativity of higher-skilled agents at work by improving their cognitive skills and psychological outcomes. In contrast, these benefits were limited for lower-skilled agents.

Contributions to the Bright Side of AI Augmentation

How organizations leverage the rapid development of AI technologies to create value has become an increasingly pressing question for researchers and practitioners. Academic research has commonly focused on organizations' use of AI to replace employees in performing various tasks (e.g., Felten et al. 2018). An attractive idea is to allow AI and employees to compensate for each other's weaknesses to generate complementarity, thus creating "augmented intelligence" (e.g., Choudhury et al. 2020; Kannan and Bernoff 2019; Kesavan and Kushwaha 2020; Puranam 2020; Raisch and Krakowski 2021; Wilson and Daugherty 2018; Lebovitz et al. 2022). This study contributes to the burgeoning literature by showing that even a simple sequential division of labor can create synergies between AI and the human employees involved. Without employees, weak AI faces limitations in independently handling high-level problem solving (Berenthe et al., 2022); without AI assistance, employees are distracted and demoralized by simple, repetitive work, whereas they desire interesting and creative work (Fleming and Sturdy 2011). The AI-human collaboration thus "kills two birds with one stone."

This study deepens the conventional vision that using AI to handle tedious and repetitive jobs will allow human employees to focus on developing more creative outcomes (Kasan 2020b; McKendrick 2021; O'Carroll 2017). We show that this desirable speculation does not always hold; theoretical tension exists over whether such AI assistance indeed increases employee creativity, but employees' domain expertise or job skills constitute a critical condition that reconciles this tension. Employees with higher job expertise benefit more from AI assistance in developing creative solutions. Thus, we enrich the theoretical insights and provide empirical evidence for this vision.

Finally, employee boredom at work is a common and problematic experience that dates back to the industrial age. The advancement of technology exacerbates this concern because it leads to further fragmentation of the work (Casilli and Posada 2019). However, this study shows that because AI technologies can effectively perform well-codified, repetitive work, they can enable employees to remain focused on more interesting work, which may result in a more meaningful work experience. Enhanced employee creativity in response to AI assistance contributes to a new channel in the literature on improving employee creativity at work (Anderson et al., 2014; Fredrickson, 2004).

Contribution to the Dark Side of AI Augmentation

Researchers are keenly aware of the "dark side" of data science and algorithms, or the potential negative consequences of these practices for workers and customers (e.g., Berente et al. 2021; Fast and Jago, 2020). Common concerns arise when AI technologies replace human workers (Felten et al. 2018; Tong et al. 2021) or render employees to carry out fragmented jobs, causing dehumanization (Kellogg et al 2020). However, we show that even when AI takes over menial, drudgery work to facilitate human employees with work that calls for creative solutions and is thus potentially interesting, concerns over the well-being and welfare of low-skilled employees heightened. These employees experienced negative emotions as they felt more tension, greater pressure, and more nervousness after receiving AI assistance in serving customers. They also experienced lower morale from failing to overcome challenges and frequent failure, making their task less interesting. They did not experience a sense of freedom to create new scripts, instead wishing for standard answers. Although they hoped for additional help from their higher-skilled colleagues, without deliberate job designs, including giving financial incentives or building a team-oriented culture (Gray et al, 2020), it is unclear why higher-skilled colleagues would devote time to providing them with the desired assistance.

Second, we highlight that AI technology's "dark side" affects human workers in a starkly unequal fashion due to the *skill-biased* outcomes of AI augmentation. Human workers with lower job skills experience "double loss"— from the lack of job skills per se and negative experience working in a team with AI. However, it is important *not* to ignore low-skilled employees because they are members of society, and many of them can grow to develop greater job skills in the future. We suggest directions for future research to investigate ways to manage AI and related processes to ensure that low-skilled employees are not left behind.

Generalizability

The sequential division of labor that we examine in the sales context is common in many other business contexts. For example, recruiters have increasingly used AI to make the first cut in the initial screening stage before human experts handle the subsequent interview stage (Elmira, Anastasia, and Marleen 2021). It has been reported that 67% of hiring managers surveyed by LinkedIn considered AI a time-saving tool (Heilweil 2019). In healthcare services that commonly use a triage process to categorize patients, AI has assisted employees with medical chart coding (Wang, Gao, and Agarwal 2019). Therefore, the presence of contexts where AI can successfully perform lower-level preparatory work as inputs for subsequent higher-level interesting work to be managed by human experts offers the necessary contexts for the predictions generated in the paper to prevail.

Employee performance is important to service organizations (Fuller & Smith, 1991; Holman et al. 2002, Lee, Batt & Mohiyan. 2019). However, in generating the theoretical framework, we did not rely on any assumption idiosyncratic to the context of telemarketing. Instead, we drew heavily on the interaction of three general pieces of literature–AI–human collaboration, job characteristics model, and employee creativity–whose logic applies to various organizations. Thus, we expect the theoretical mechanisms developed in this context to be relevant to many other organizational contexts that can implement the abovementioned division of labor between AI and human employees.

Limitations and Future Research

More sophisticated forms of AI-human collaboration may involve allowing humans and AI to use or modify the content of others' work (e.g., Choudhury et al. 2020, Jussupow et al. 2021; Kesavan and Kushwaha 2020). Research on such direct interactions between human workers and AI in organizations focuses on what human workers do with AI-generated information (Lebovitz, Lifshitz-Assaf, and Levina 2021; Waardenburg, Huysman, and Sergeeva 2022) and how developers and users of AI co-create technology (van den Broek, Segeeva, and Huysman 2021; Singer, Kellogg, Galper, and Viola 2022). Can direct interaction between AI and human workers enhance employees' creative or innovative outcomes? On the one hand, human workers can "stand on the shoulders" of AI-generated predictions about the structured components of their tasks, which could enable them to explore new ideas. On the other hand, human workers have limitations in fully understanding AI's work (Waardenburg, et al 2022) and may stay unengaged with it (Lebovitz et al. 2021), thus hindering their exploration. However, this tension warrants further investigation.

Although both the domain knowledge and psychology of human workers are important to how they understand, use, and interact with AI (Singer et al 2022; van den Broek et al. 2021, Lebovitz et al 2021), we show that human workers' domain knowledge or job skills critically condition AI's effect on their psychological outcomes. Which is more critical to the productive adoption of AI in organizations—training human workers with proper domain knowledge or helping them tackle psychological obstacles? Furthermore, does the preparation of necessary domain knowledge need to be coordinated with the right mentality for human workers in AI adoption? These questions deserve further attention.

Finally, curbing the dark side of AI adoption requires firms and managers to better design the adoption of AI (Kellogg et al., 2020). For example, complementary investments accompanying AI adoption may be warranted in the form of extra training for lower-skilled employees. Since low job skills lead to "double loss," elevating job skills generates duplicative returns for employees and the firm. Another type of complementary policy is to create incentives and a culture for creative outcomes generated by higher-skilled employees under AI assistance to spread more widely.

CONCLUSION

AI technologies may assist employees in becoming more creative by generating new and useful ideas at work, but starkly more so for employees with higher job skills. Thus, AI-augmented employee creativity is skill-biased. We provide causal evidence from a field experiment in a telemarketing firm and enrich the theoretical mechanisms through a qualitative study using semi-structured interviews. We highlight the value created by AI-human collaboration in enhancing human creativity (which is key to the Fourth Industrial Revolution) and the unequal effects on human workers with varying existing job skills, which deserve greater attention from scholars, practitioners, and policymakers.

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Figure 1. Theoretical Framework

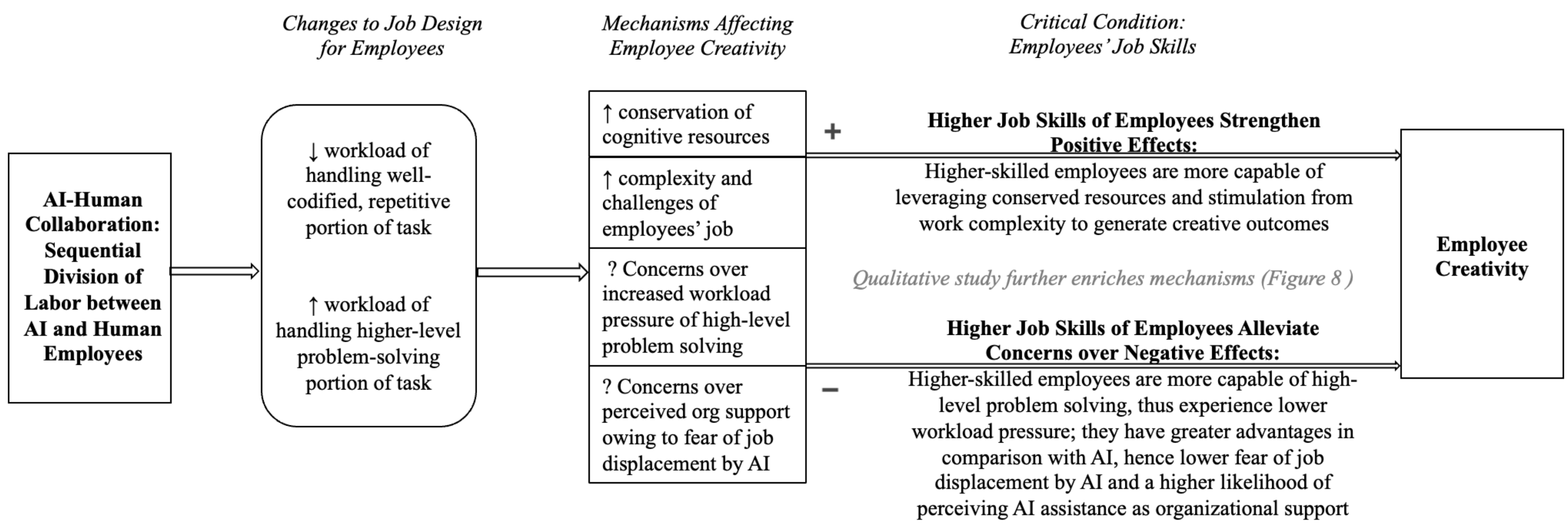


Figure 2. Experimental design

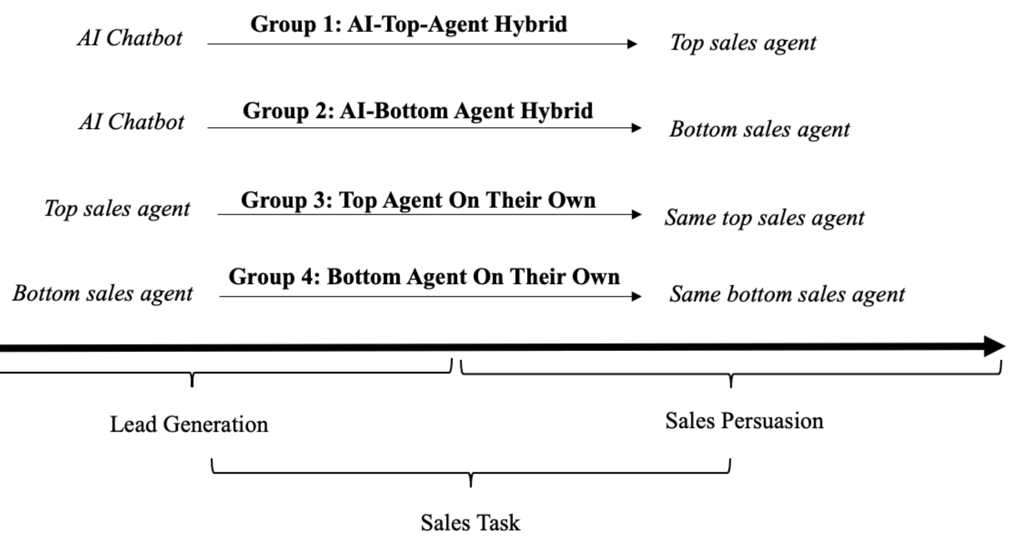


Figure 3. Comparison of agents and AI-assisted agents in solving outside-knowledge-bank questions

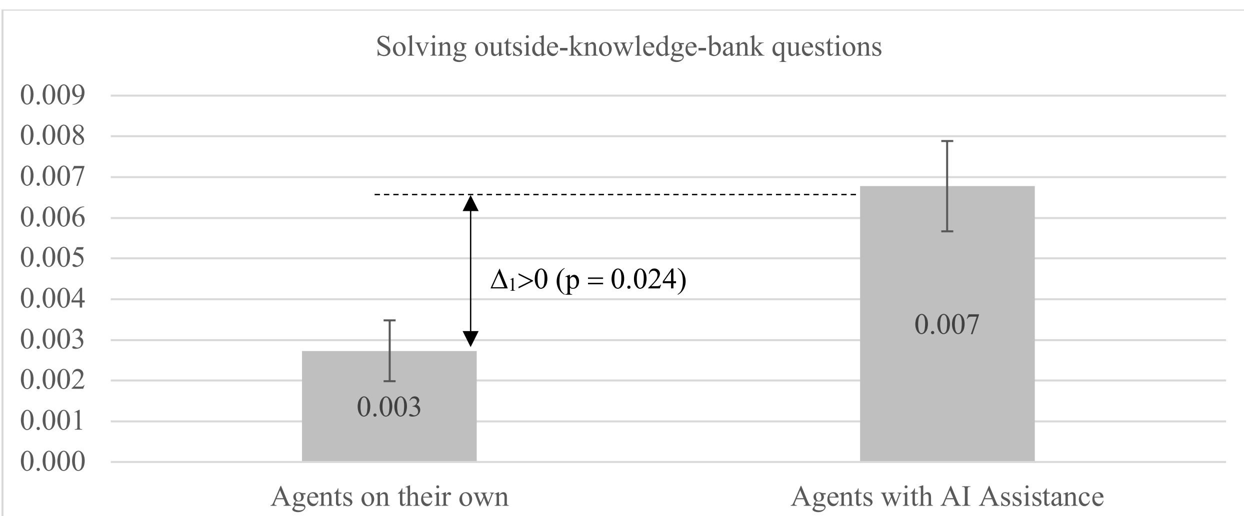


Figure 4. Comparison of top vs. bottom agents, with and without AI assistance in solving outside-knowledge-bank questions

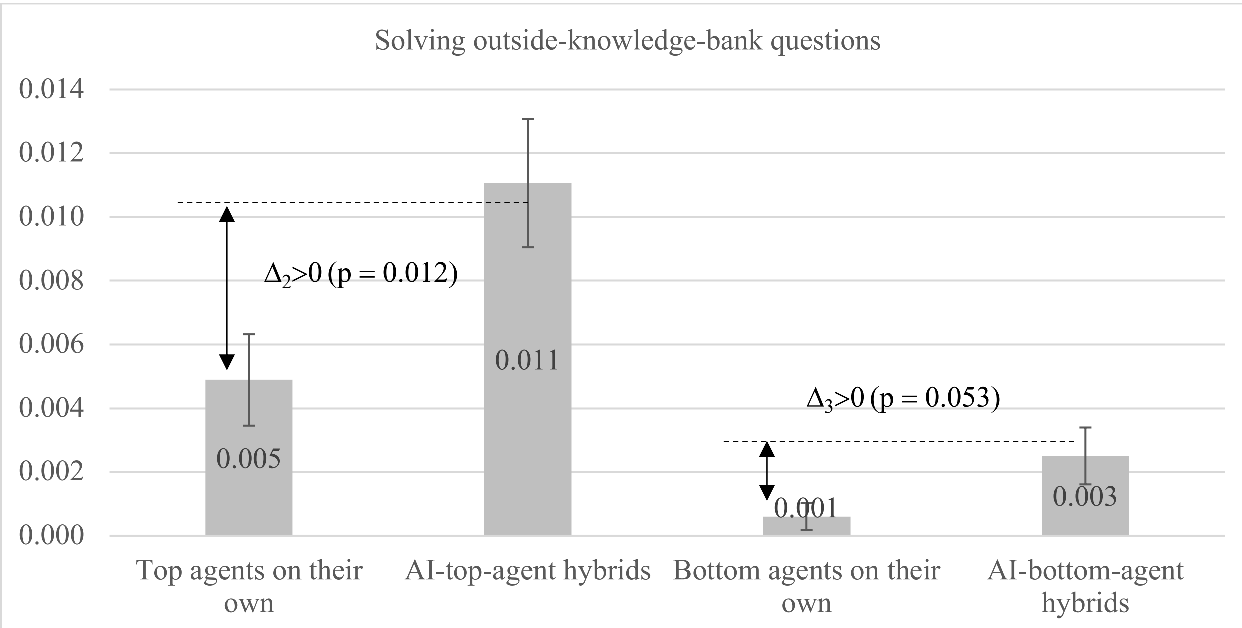


Figure 5. Validity check: solving outside-knowledge-bank questions for cold-call vs warm-call customers

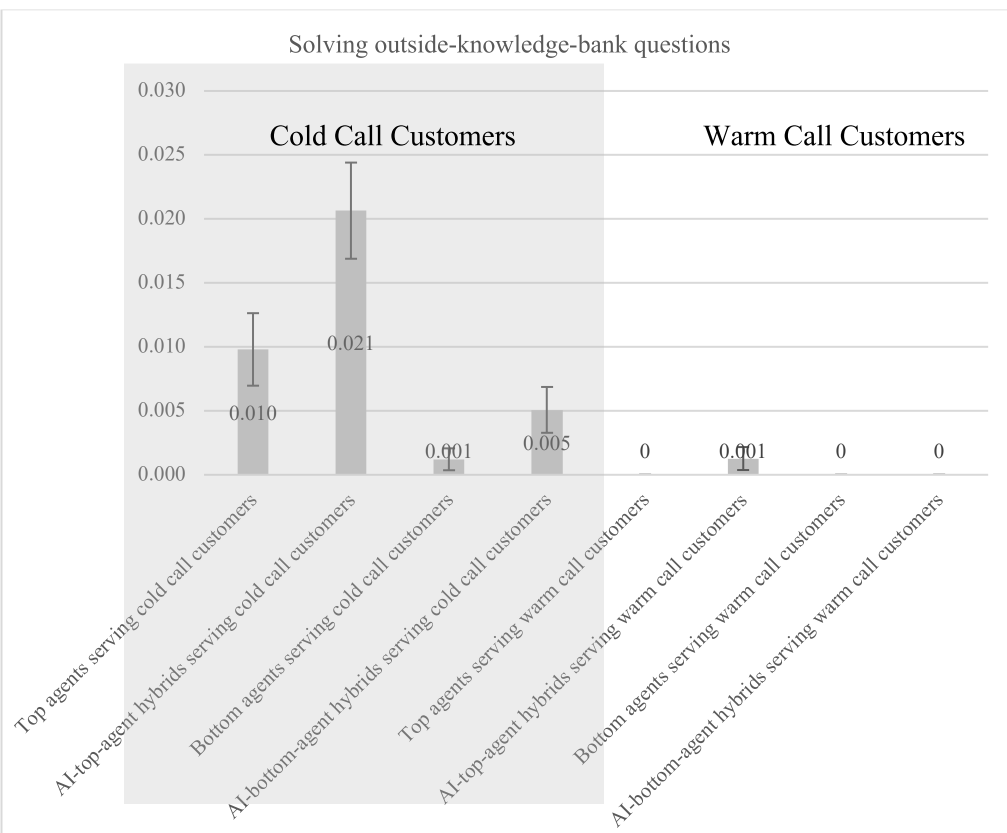


Figure 6. Comparison of performance outcomes

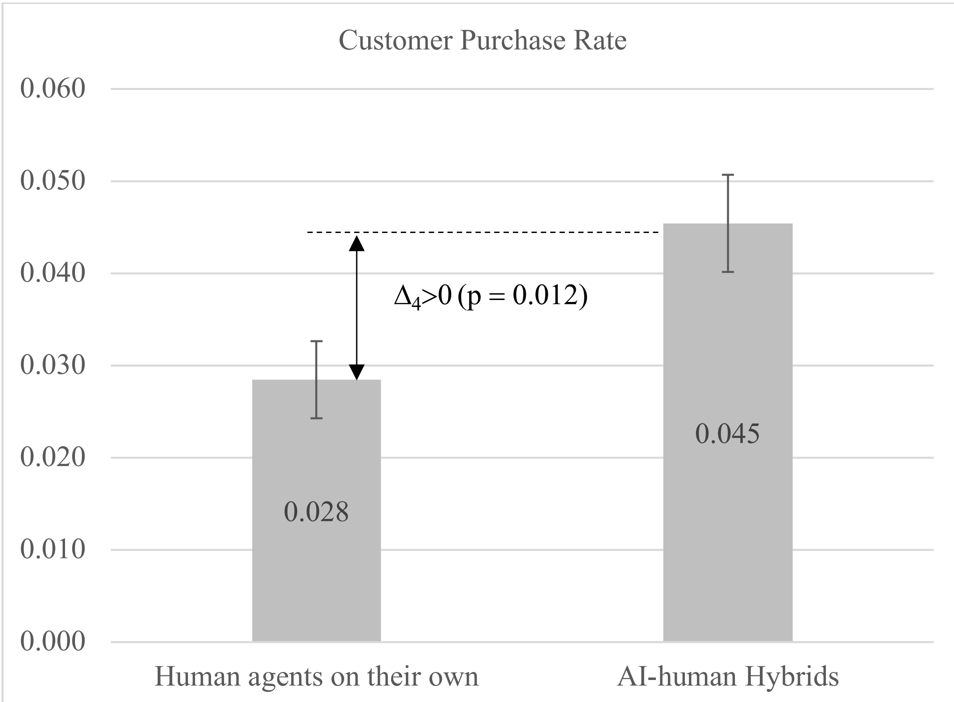


Figure 7. Summary of causal mediation analysis results

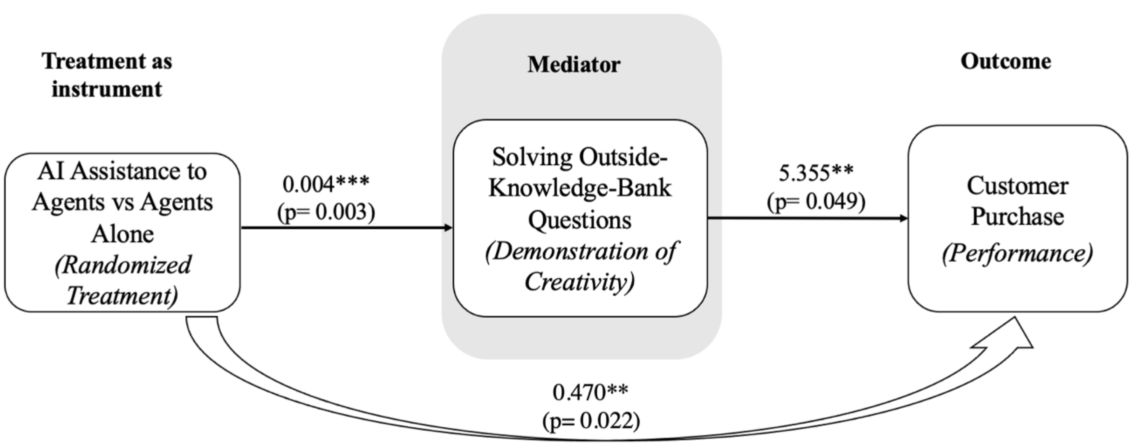
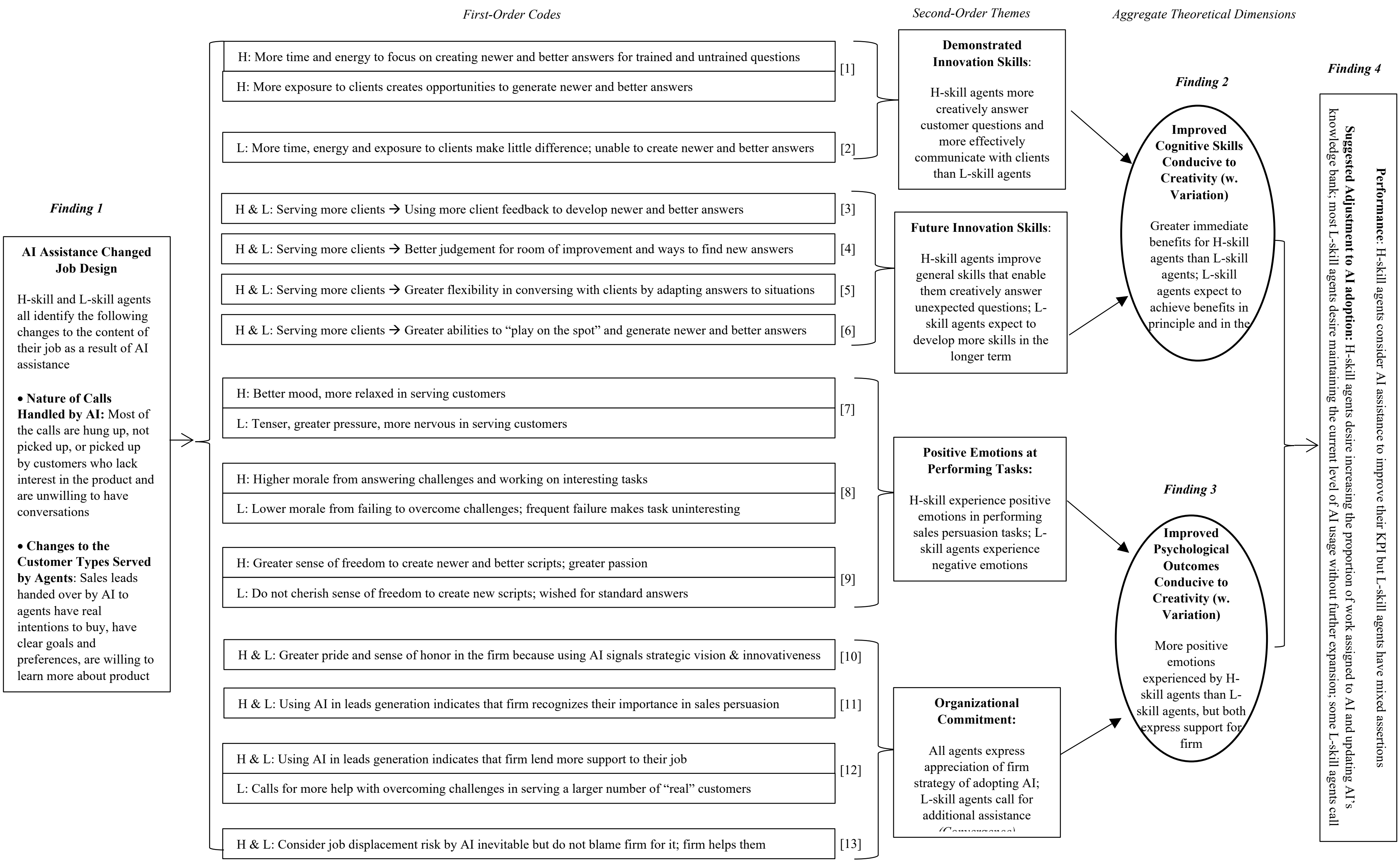


Figure 8. Data Analysis of Semi-structured Interviews



Notes: “H” and “H-skill agents” stand for high-skilled sales agents; “L” and “L-skill agents” stand for low-skilled sales agents.

Table 1: Summary Statistics and Pairwise Correlations

	Panel A	Obs	Mean	Std	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	*Solving Outside-knowledge-bank Questions*	3,144	0.04	0.19	0	1	1							
(2)	*Customer Purchase*	1,528	0.00	0.03	0	0.29	0.07	1						
(3)	*AI-Human Hybrid*	3,144	0.50	0.50	0	1	0.08	0.05	1					
(4)	*Top Agent*	3,144	0.50	0.50	0	1	0.12	0.05	0.00	1				
(5)	*Age*	3,144	30.88	6.50	19	55	0.00	0.02	0.00	-0.01	1			
(6)	*Education*	3,144	2.79	0.83	1	4	0.03	0.01	0.00	0.01	-0.02	1		
(7)	*Gender*	3,144	0.51	0.50	0	1	-0.01	-0.02	0.02	0.00	-0.02	0.01	1	
(8)	*Other Credit Cards*	3,144	0.25	0.43	0	1	0.00	0.01	0.01	0.00	0.02	-0.05	-0.03	1
(9)	*Disturbed by Transition*	1,487	0.27	0.44	0	1	0.00	-0.01	-0.01	0.02	0.03	-0.04	0.02	0.02

Table 2: Randomization Check

Panel B	N	*Age*	*Education*	*Gender*	*Other Credit Cards*	*Disturbed by Transition*
Served by top agents on their own	783	30.89	2.79	0.50	0.25	0.26
Served by AI-top-agent hybrid	776	30.76	2.81	0.52	0.25	0.30
Served by bottom agents on their own	798	30.81	2.79	0.50	0.25	0.29
Served by AI-bottom-agent hybrid	787	31.05	2.77	0.51	0.26	0.23
Prob > F		0.83	0.90	0.75	0.93	0.12
Prob > Chi Square		0.18	0.35	1.00	0.96	0.33

Note: *Age* is the age of the customer; *Education* refers to customers highest degree attained (1=High school degree, 2=junior or community college degree, 3=bachelor's degree, 4=post graduate degree); *Gender* refers to customer's gender (0 = female; 1 = male); *Other Credit Cards* indicate if the customer owns other credit cards (0 = no; 1 = yes); *Disturbed by Transition* indicates if the customer reports feeling disturbed by the experience of being handed over to another agent for sales persuasion (0 = no; 1 = yes).

Table 3. Employee Creativity Outcomes

DV: Solving outside-knowledge-bank questions

	(1)	(2)	(3)	(4)	(6)	(7)
Sample	All	All	All	All	Sub-Sample: Involving top agents only	Sub-Sample: Involving bottom agents only
AI-Human Hybrids		0.004**	0.004***	0.002**	0.006**	0.001*
		(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
Top Agents			0.007***	0.004**		
			(0.001)	(0.002)		
*AI-Human Hybrids * Top Agents*				0.005*		
				(0.003)		
Age	0.000	0.000	0.000	0.000	-0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Other Credit Cards	-0.000	-0.000	-0.000	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Education	0.001	0.001	0.001	0.001	0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender	-0.000	-0.001	-0.001	-0.001	0.001	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Disturbed by Transition	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)
Constant	0.002	0.000	-0.003	-0.002	0.001	-0.001
	(0.004)	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)
Observations	1487	1487	1487	1487	739	748
R2	0.001	0.007	0.024	0.026	0.012	0.015

Standard errors clustered at the agent level, reported in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Supplemental Materials for

When and How Artificial Intelligence Augments Employee Creativity

by

Nan Jia
Xueming Luo
Zheng Fang
Chengcheng Liao

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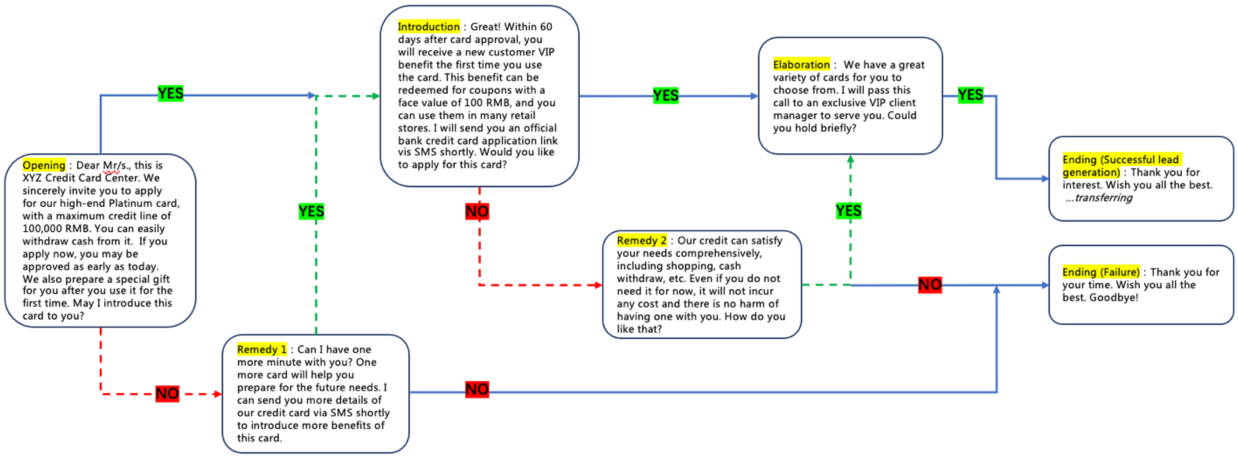
Appendix 1: An example protocol of sales leads generation



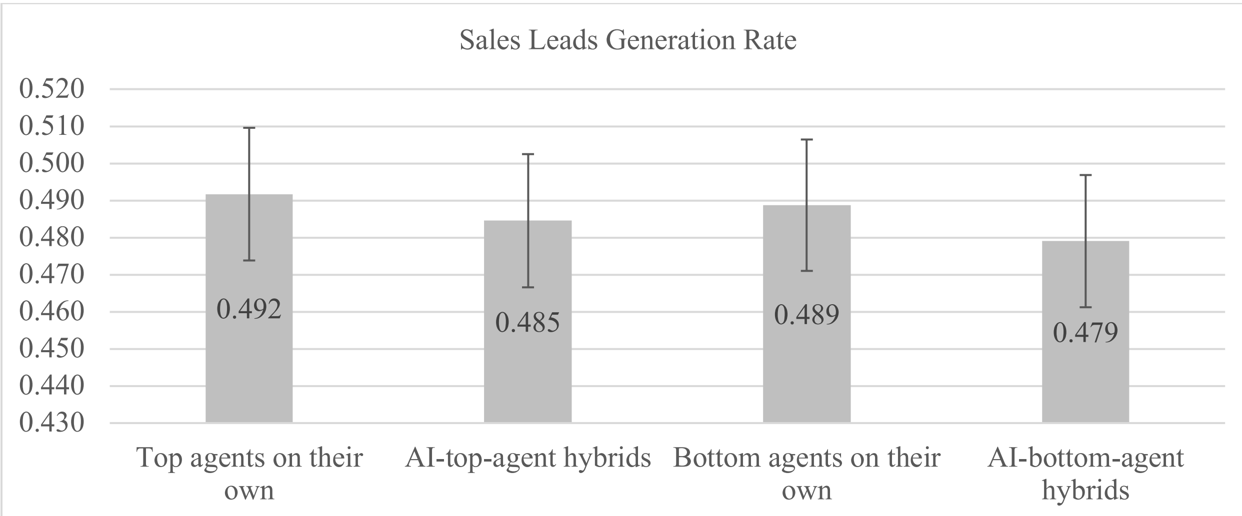
Appendix 2. Results of Multilevel Models

Multilevel regression with random effect at the agent level
DV: Solving outside-knowledge-bank questions

	(1)	(2)	(3)	(4)	(6)	(7)
Sample	All	All	All	All	Sub-Sample: Involving top agents only	Sub-Sample: Involving bottom agents only
AI-Human Hybrids		0.004^{**}	0.004^{***}	0.002	0.006^{**}	0.001
		(0.002)	(0.001)	(0.002)	(0.003)	(0.001)
Top Agents			0.007^{***}	0.004^{**}		
			(0.001)	(0.002)		
*AI-Human Hybrids * Top Agents*				0.005^{*}		
				(0.003)		
Age	0.000	0.000	0.000	0.000	-0.000	0.000^{*}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Other Credit Cards	0.000	0.000	-0.000	-0.000	0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)
Education	0.001	0.001	0.001	0.001	0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender	-0.000	-0.001	-0.001	-0.001	0.001	-0.002^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)
Disturbed by Transition	0.000	0.000	0.000	-0.000	-0.000	-0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)
Constant	0.002	0.000	-0.003	-0.002	0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.008)	(0.003)
Observations	1487	1487	1487	1487	739	748
R2	0.001	0.007	0.024	0.026	0.012	0.015

Standard errors clustered at the agent level, reported in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

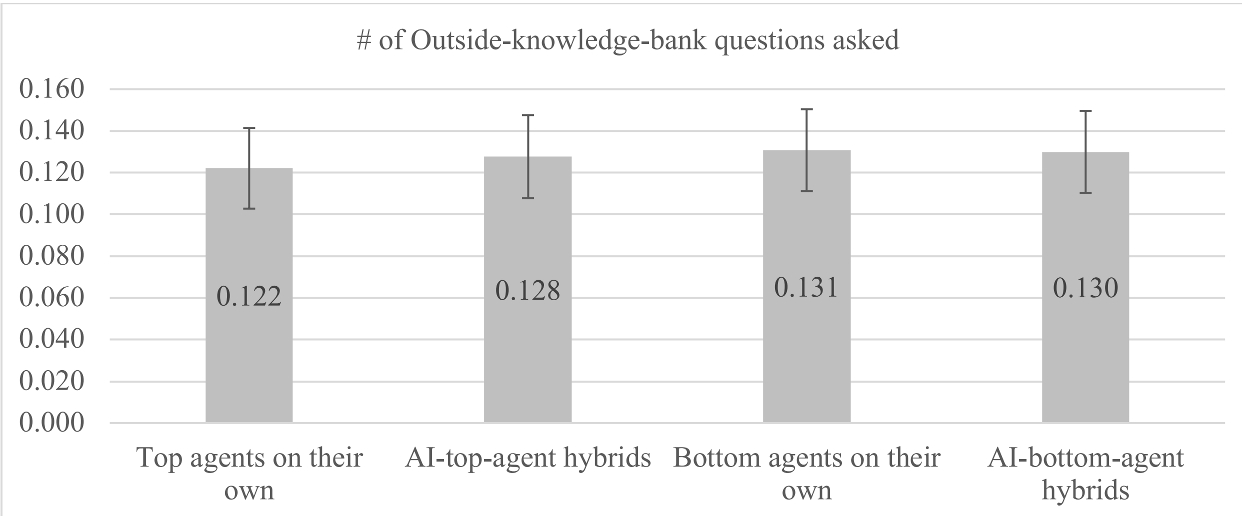
Appendix 3: Addressing alternative explanations – sales leads generation among experimental groups



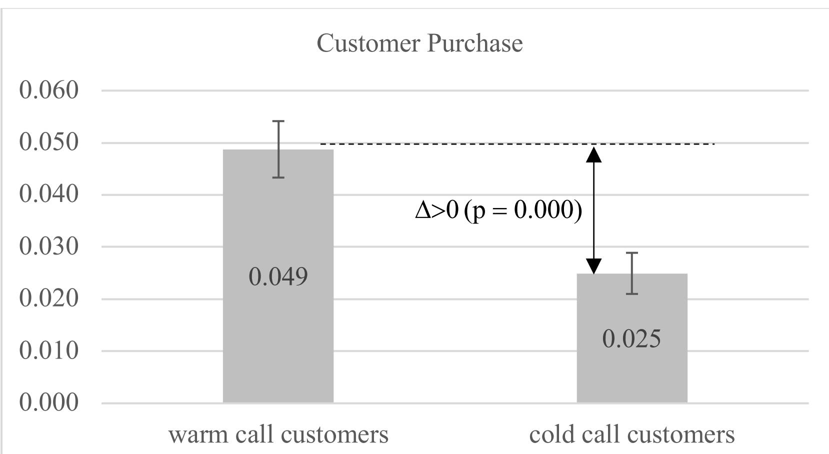
Appendix 4: Characteristics of sales leads (customers who confirmed their interest at the first stage) across four experimental groups: one-way analysis of variance (ANOVA)

	N	*Age*	*Education*	*Gender*	*Other Credit Cards*	*Disturbed by Transition*
Served by top agents on their own	385	30.76	2.78	0.51	0.25	0.26
Served by AI-top-agent hybrid	376	30.84	2.77	0.52	0.26	0.30
Served by bottom agents on their own	390	31.23	2.80	0.51	0.25	0.29
Served by AI-bottom-agent hybrid	377	31.11	2.70	0.53	0.28	0.23
Prob > F		0.74	0.36	0.92	0.74	0.12
Prob > Chi Square		0.20	0.56	1.00	0.87	0.33

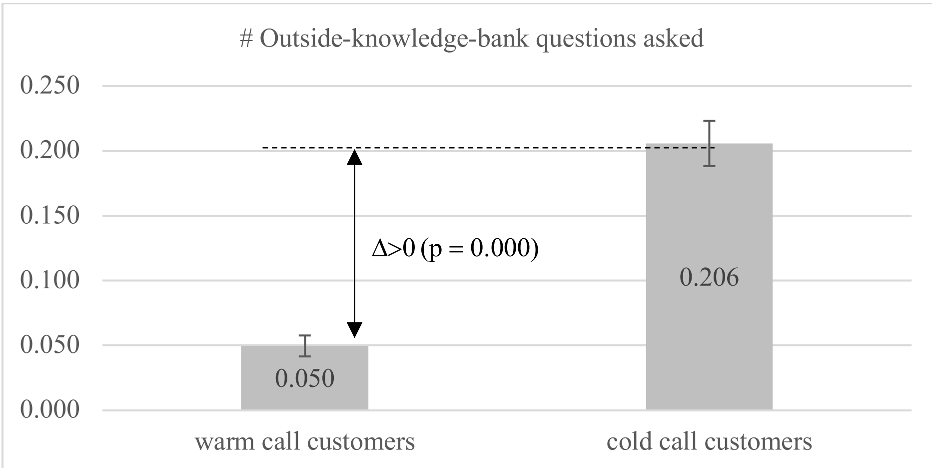
Appendix 5: Addressing alternative explanations – Number of outside-knowledge-bank questions *asked* among experimental groups



Appendix 6: Validity check – Customer purchase rate by cold-call vs warm-call customers



Appendix 7: Validity check – outside-knowledge-bank questions asked by cold-call vs warm-call customers



Appendix 8. Results of Causal Mediation Analysis

Treatment Effect on the Mediator	
AI-Human Hybrid	0.004***
	(0.001)
Age	0.000
	(0.000)
Other Credit Cards	0.000
	(0.002)
Education	0.001
	(0.001)
Gender	-0.001
	(0.001)
Disturbed by Transition	0.000
	(0.002)
Constant	0.000
	(0.004)

Mediated Effect on Customer Purchase	
AI-Human Hybrid	0.470**
	(0.206)
Solving Outside-knowledge-bank Questions	5.355**
	(2.717)
Age	0.018
	(0.014)
Other Credit Cards	0.016
	(0.227)
Education	0.150
	(0.124)
Gender	-0.244
	(0.202)
Disturbed by Transition	-0.042
	(0.229)
Constant	-3.699***
	(0.621)
N	1487
Total Effect Mediated	0.044

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix 9. Semin-Structured Interview protocol

The third and the fourth authors directly participated in and closely managed the interviews, by (a) conducting initial interviews; (b) providing training to research assistants, who were PhD students in a large research business school, to conduct interviews; (c) closely monitoring the interview process by reviewing the transcript of each interview immediately after it was completed and providing feedback to interviewers; and (d) providing answers and support to questions raised by interviewers.

The questions in the interview guide were *not* used as a questionnaire but as a guide to help interviewers initiate conversations followed by questions to clarify or probe into the given answers. More questions were asked than those included in the interview guide based on open dialogues and the interviewees' responses. The interviewers emphasized building relationships with interviewees and encouraged them to express their thoughts and emotions, and elaborate on specific examples and stories.

Protocols for Interviewers

Important notes for interviewers:

- It is important to cover each topic below (in red).
- However, within each topic, there is *no need* to ask every single one of the sample questions. The sample questions are *not* meant to be an exhaustive list of all questions that interviewers could and should ask (i.e., this is *not* a survey questionnaire). Instead, sample questions offer useful suggestions on how to start the conversation on each topic. Some of them will become irrelevant as the conversation proceeds, depending interviewees' response. Moreover, spontaneous follow-up questions that exceed the scope of the list of questions may be—and should be—asked (see next point).
- Based on interviewees' response, follow-up questions *always* need to be asked whereas some follow-up questions are spontaneous and are thus not included in this list of sample questions. Please be prepared to capture the opportunities to learn about new issues on the fly. Please bear in mind that due to the nature of semi-structured interviews, *unanticipated* and *spontaneous* opportunities to ask unscripted questions often emerge.
- The focus here is to let interviewees express feelings and emotions, and to encourage them to use examples and stories to explain how they feel.

Background questions

- How long have you been working for this firm? What products have you sold so far?
- Is selling credit cards similar to or different from selling other products, based on your own experience? What are the similarities and/or differences?

Answering questions from customers that fall within or outside the scope of training

[The following two sets of questions are for interviewing all agents, including those who received or did not receive AI assistance.]

- Did any customers ask any questions that you were not being trained for? Example(s)? How did you answer them?
  [Note to interviewer: try to ask and follow up with as many mentions of untrained questions as possible because they occur less frequently than trained questions.]

  - Do you think you successfully addressed the question(s)?
    - Looking back, would you have done differently? How? Why?
  - What circumstances could enable you to address those questions more satisfactorily?

    [Note to interviewer: We raise a couple of sample questions below. Do not lead with these sample questions; use them as examples only if interviewees seem confused or request clarification. Do not constrain interviewee with these questions. Instead, encourage them to share and talk freely.]

    - For example, if you had more time to think about it, do you think you would have addressed the question more effectively?
    - For example, if you were somehow able to concentrate better at that moment, would you have responded differently?

- For questions that customers asked and you have been trained to answer, did you handle them successfully? Any question that you would have handled differently, in retrospect? Example(s)?
  - If there are questions that you wished you handled differently, looking back, what could have enabled you to better handle it on the spot? Why? Example(s)?

[The following two sets of questions are *only* for interviewing agents who received AI assistance]

- How do you feel about AI assistance—that AI reach out to customers and hand over confirmed leads to you? Example(s)?
  [Note to interviewer: Please cover all bullet point below but be prepared to follow up with interviewees on what they say, by asking additional questions. Please note that one answer may pertain to multiple bullet points. Do not *feel obligated to cover these bullet points in the same order as listed here. Encourage interviewees to share stories and feelings.]*

  - Do you prefer this way, or do you prefer to reach out to customers on your own to generate sales leads, like you did in the past? Why? Example(s)?
  - Does having AI generating sales leads (instead of yourself) somehow make your life easier or more difficult? Why/why not? Example(s)?
  - Do you have any concerns about using AI assistance in this way? Does it hinder your work in any way? Does it help with your work in any way? Example(s)?
  - How does having AI generate sales leads (instead of doing it on your own) affect the way you address **untrained** questions? Why/why not? Example(s)?
    - Does it make it easier or more difficult for you to handle those questions?
  - How does having AI generate sales leads (instead of doing it on your own) affect the way you address **trained** questions? Why/why not? Example(s)?
    - Does it make it easier or more difficult for you to handle those questions?
  - If sales leads were generated by other colleagues instead of the AI chatbot, would it make a difference to you? Would it affect how you handled your part of the sales?

- How do you feel about the company's practice of adopting AI to generate sales leads?

[Note to interviewer: Please cover all bullet points below, but it is very important to be open to all sorts of feedback and feeling. Encourage interviewees to share stories and feelings.]

- Is it a good thing for employees that your company adopts these AI chatbots to generate sales leads for employees to serve? Why/why not? Example(s)?
    - Are you happier to have AI assistance than no such assistance? Why/why not? Example(s)?
    - Does the adoption of AI chatbots in this fashion concern you in any way? Example(s)?
- Does this practice change how you feel about the company? How?
  [Note to interviewer: We raise a sample question below. Do not lead with this sample questions; use it as an example only if interviewees seem confused or request clarification. Do not constrain interviewee with this question. Instead, encourage them to share and talk freely.]

    - E.g., Do you feel that with this practice, the company aims to give you more support?

Future: open ended questions

- Do you prefer to continue to have AI chatbot generate sales leads for you? Why/why not?
- Should the company increase/maintain/decrease of the use of AI chatbot to generate sales leads? Why?
- Would you use the AI chatbot in a different way? If so, what is your suggestion(s)?
- Other thoughts to share?

Appendix 10. Summary of Interview Quotes

<table>
<tr><th colspan="2"></th><th>Quotes from High-Skilled Agents</th><th>Quotes from Low-Skilled Agents</th></tr>
<tr><td rowspan="3">AI changes job design</td><td>Feature of lead generation</td><td colspan="2">“…is hard labor…[because] if you reach out to customers by yourself, there will be many situations including connection failures, customers hanging up on you, and customers scolding you upon picking up the calls” (#H5)

“you rarely have real communication with customers” (#H1)

Lead generation “requiring no skills” (#L1) and “highly-frequent but minimally-effective communication” (#H13)

Conversations with customers were “seldom” (#L5) because agents spent most of their time “trying to get connected, [dealing with] hang-ups, and having very short conversations if customers even picked up the calls” (#L13)</td></tr>
<tr><td>Feature of sales persuasion</td><td colspan="2">Customers “had clear ideas about what they want” (#H9), “were truly willing to listen to [agents’] introduction [of the product]” (#H6), and thus of “high value” (#H13)

Agents’ “likelihood of actually engaging in conversations with customers is almost 100%” (#L3)

Handing sales persuasion without lead generation “increased the intensity and challenges of [agents’] work” (#L14)</td></tr>
<tr><td>Overall impact of changed job design</td><td>Although with AI assistance, “the difficulty of the content of [their] work has increased” (#H7), agents considered this change “a good thing for [their] efficiency and performance” (#H7) and commonly reported feeling “elated…because this changed work mode significantly helps and improves [their] work” (#H13)

“After all, for us, dealing with those boring, non-technical things [lead generation] every day is a bit overkill. We should be assigned to a more difficult business.” (#H12)

“I have no problem dealing with questions that I have been trained on, but I think we need to have more opportunities to contact customers. Only after communicating with customers can I know what problems exist, how to deal with those problems, and then think about it repeatedly to further improve my scripts, invent new scripts, and better deal with these problems when I encounter them again in the future.” (#H11)</td><td>“[AI assistance] only reduces our work efficiency because AI has processed all the simple and unskilled tasks, and all the subsequent cases require a certain level of skills in [using the right] scripts, so we will naturally be much slower to process the cases. The duration of serving each customer increases, and the number of customers we can serve is significantly reduced.” (#L2)

“Although the frequency of communication with customers increases, the difficulty of customers’ questions raised during the communication process also increases. I am more likely to become stuck without knowing how to answer the questions raised by customers. It may make customers feel that I am less professional; thus, for me, the sense of pressure is multiplied, and I must learn as soon as possible to catch up.” (#L10)

“It’s like putting a doctor who only sees outpatients in the ICU to care for patients. There is a feeling of driving the duck on a perch. First and foremost, I do not have strong skills, and I easily become nervous when I encounter difficult clients. When I become nervous, I do not know what to do next. So, I am a little worried about failing to serve potential customers well.” (#L7)</td></tr>
</table>

(Appendix 10 Cont'd)

<table>
<tr><th></th><th></th><th>Quotes from High-Skilled Agents</th><th>Quotes from Low-Skilled Agents</th></tr>
<tr><td rowspan="6">AI-Induced Development of Cognitive Skills Conducive to Creativity</td><td>Time and concentration</td><td>AI assistance enabled agents to "devote more time and stay more concentrated on thinking about how to resolve questions [that were challenging]" (#H9)

"AI assistance freed up more time for us to think more about how to overcome some difficulties. For example, when there was no AI assistance, about half of our day was spent dialing numbers and dealing with no answers, hang-ups, short conversations, and so on. Thus, we could not handle many real cases in one day. However, after AI intervenes, we can also handle the same number of cases in one day as we previously did but have a lot more time to think." (#H6)

"When I have sufficient time, I can think more comprehensively, and the answers to the questions are better… when I can concentrate better, my thinking will be more focused, and my answers to some on-the-spot questions should be more accurate." (#H1)

"With the assistance of AI, we are liberated from tedious and repetitive calls to better focus on serving willing customers. We have more time and freedom to improve our skills and innovate our scripts continuously." (#H3)</td><td>"Paying more attention and spending more time [on solving questions] probably do not make a difference; I can't think of a better solution." (#L5)

"Even with more time, I am not sure if I can find a better solution because solving some problems does not necessarily hinge on spending more time to think but on my limited abilities." (#L6)

"I have low ability and a weak foundation, and it is difficult for me to innovate when encountering challenging cases." (#L1)</td></tr>
<tr><td>Job complexity</td><td>"There is a saying that 'knowledge comes from practice.' By constantly encountering problems in real businesses, solving them, and accumulating experience from serving challenging customers, we can continuously improve and innovate the content of scripts. Without AI assistance, we will not have that much time to interact with these valuable customers to update our answers to questions." (#H9)

"[AI assistance] stimulates my creativity because I now more frequently encounter important and difficult problems. For the problems that we have been trained for, I can provide different solutions, continue to innovate them, and replace existing solutions with better ones." (#H5)</td><td>Observing highly skilled colleagues solving challenging questions by developing new, innovative answers:

"[I benefit from] the scripts developed by higher-performing colleagues. As AI manages cases that do not require skills, the remaining cases passed to humans are relatively more difficult. It is difficult for us to innovate for these cases, but my higher-performing colleagues can continue to break through and innovate, and it will also benefit us." (#L14)

"In fact, [AI assistance] can indeed help us to explore see if we can innovate the answers to the problems for which we have been trained. Although I cannot do that myself, I have seen some outstanding colleagues coming up with new answers."</td></tr>
<tr><td>Customer feedback</td><td colspan="2">"The more we contact customers who are willing to communicate, the greater the amount of information we obtain from them, and the more we can review and innovate our business through iterations." (#H2)</td></tr>
<tr><td>Identify opportunities</td><td colspan="2">"We can accumulate more experience of serving complicated cases, which provides ideas for how to innovate in the future; the more customers we serve, the more we can judge whether there may be room to adjust the existing, trained way of solving problems." (#L14)</td></tr>
<tr><td>Flexibility</td><td colspan="2">"After all, I have gained more practical experience and thus can handle problems more flexibly." (#H5)</td></tr>
<tr><td>"Play on the spot"</td><td colspan="2">"The key to dealing with problems on the spot is to have enough actual 'combat experience' so that we do not panic, and we can readily use our skills to 'get the man.' Therefore, to deal with these problems well, we need to accumulate rich experience." (#L2)</td></tr>
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(Appendix 10 Cont’d)

<table>
<tr><th colspan="2"></th><th>Quotes from High-Skilled Agents</th><th>Quotes from Low-Skilled Agents</th></tr>
<tr><td rowspan="5">AI-induced Psychological Outcomes Conducive to Creativity</td><td>Mood</td><td>They experience “a greater sense of relief” and “a better mood” (#H6) because hey no longer needed to conduct “repetitive, tedious, and meaningless” (#H5) phone calls for lead generation, which they found “frustrating” (#H7): “The work in the previous stage is always hard labor. If processed by humans, emotional fluctuations are inevitably generated. …it is a waste of my time and energy” (#H5)

“[With AI assistance,] all the customers whom I handle have intentions [to buy] and are willing to listen to my introduction. When chatting with them, I feel much more relaxed, and I am in a much better mood; thus, naturally, I feel that pressure at work is much reduced, and I feel greater relief and pleasure.” (#H6)</td><td>“I don’t feel relieved. However, it makes life more stressful because I have to deal with many more complex businesses. They give me headaches throughout the day; how can I be more relaxed?” (#L9)</td></tr>
<tr><td>Morale</td><td>boosted “moral of combat” or “fighting spirit” (e.g., #H5, #H13)

“This approach [using AI assistance] makes me feel that our work is quite challenging. After adopting AI assistance, we focus on dealing with more difficult problems, but the more challenging the customers are, the more motivated we are, and the more work we want to do.” (#H3)</td><td>Serving more challenging customers “interfered with [their] mentality at work, making it more difficult for [them] to do business in the future” (#L11)

“Judging from my current performance, the customers who have passed the AI screening are a big challenge for me, and I am not always able to ‘overcome’ them. Thus, it is difficult to stimulate my fighting spirit. Conversely, it can make me lose confidence in my work.” (#L14)

“In addition to amping up pressure, [a change of work mode] gradually destroys my fighting spirit because the difficulty of the cases is too great, my progress is too slow, and the outcomes are not desirable. Thus, the work becomes increasingly less engaging.” (#L2)</td></tr>
<tr><td>Passion</td><td>Increased “work motivation” (#H9) and greater “passion” (#H6)

“We have more opportunities to encounter difficult and challenging questions from customers, some of which are not in the knowledge bank; without the restrictions of the knowledge bank, we have more freedom to be innovative [with new scripts].” (#H2)</td><td>“It would be best if there was a standard answer to every question encountered” (#L9).</td></tr>
<tr><td>Perception of firm’s adoption of AI</td><td colspan="2">“a sense of pride” and “a sense of honor” (e.g., #L3, #L14, #H6, #H13)

“[AI assistance] makes me feel more superior because AI is a big trend now, and the company is constantly innovating. Working in such a company makes me feel like I am at the frontier of our time, being fashionable and not rustic, just like buying the latest mobile phone models. My sense of pride naturally arises. Although other companies, such as Railway Construction Corporation and Sanitation Company, are large in scale and have state-owned enterprise backgrounds, they sound like yokels. I can even show off to my friends. I feel enthusiastic about working in such a work environment.” (#H9)</td></tr>
<tr><td>Firm’s recognition of agents</td><td colspan="2">Using AI to give assistance to agents shows firm’s “recognition of [their] job skills” (#H33) and that the firm considered them to be “an indispensable part of the business” (#H33). It means that “[t]he company still thinks highly of [their] work skills” so that they felt “proud to be assigned such complex and difficult cases” (#L4).</td></tr>
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	Organizational support	the company “certainly gave us more support in business and laid the foundation for us to communicate with customers. At least the purpose of our communication does not need to be explained [to customers], so customers may become more likely to cooperate with us” (#L2) “I think [by adopting AI] our firm wants us to have more opportunities to meet and communicate with real customers, so we don’t have to repeat those high-frequency scripts.” (#L10)	
	Threat of substitution by AI	“In the short term, [AI assistance] is a good thing, but in the long run, there will be threats. Although AI assistance with our work has helped improve work efficiency and capabilities, will it replace us when AI becomes even more mature in the future? Everyone understands this possibility, but current AI technology has been widely used, and it is correct for the company to adopt AI; otherwise, the company itself may be eliminated. Even if this stage [AI displacing agents] is reached in the future, it will be a necessary decision by the company for technological progress. If there are opportunities, we can choose to transfer them to different positions.” (#H13) the company’s adoption of AI “an inevitable trend” (#L4) that was imperative for “the company’s own survival” (#L1); thus, “the company’s thinking is reasonable: the company needs to grow in the long run, the employees need to continuously make progress, and the new technologies need to continuously expand” (#L9).	
Performance Consequences		Contrast between their work post- and pre-AI adoption as one of “high efficiency and high quality versus low efficiency and low quality’ (#H13)	“In the past, the volume of business was large, and the success rate was low. Now, although the volume of business [that I can handle] reduced less, the success rate can be much higher” (#L1).
Suggested Changes to AI Adoption		Suggest expanding the use of AI to handle more “ineffective calls that otherwise occupied too much of our time” (#H2) “[AI involvement] can be maintained [at the current level] for now and gradually increased. As some of the difficult problems that we have encountered are not in the AI knowledge bank, [the company] needs us to continue summarizing our experiences and iteratively update the knowledge in the AI library” (#H11).	“if it continues to increase, the jobs that are left for us to handle will become even more difficult, and I am not sure if I can complete them” (#L3) “From the company’s perspective, [the use of AI assistance] should increase. As previously mentioned,, this is a trend. From my personal perspective, it is good to maintain [my current level]. After all, those of us with poor performance need to be left with some work to do.” (#L10)

Notes: The interviews were conducted in the local language. The first and second authors who were native speakers of the local language translated the transcripts into English and cross checked the quality of translation.

Appendix 11: A different research question: A "horse race" between AI and human agents for sales persuasion

The main paper focuses on AI-human collaboration, with the research goal of examining how AI's assistance with lead generation, the initial stage of the sales task, affects employees' creativity demonstrated during sales persuasion, the subsequent stage of the same sales task. While in the main paper we do not intend to study how AI compares with human agents in performing the subsequent stage of sales persuasion, we indeed have an experimental group in which the AI chatbot engaged in both lead generation and sales persuasion, without any human agents involved. We note, however, that because of the absence of human involvement, insights generated by this treatment group do not directly help us address the research question of the main paper, which hinges on human agent's creativity demonstrated during sales persuasion. Thus, the discussion below addresses a different research question—a "horse race," instead of collaboration, between AI and human agents. We have briefly discussed our findings in Footnote 6 of the main text, and we report more details on our theoretical expectations and empirical results.

As discussed in the main text, unscripted questions are more likely to occur during sales persuasion than lead generation. Current AI technologies have a weaker ability to solve unscripted questions, although they are competent in handling scripted questions for which they have been trained with. In contrast, greater job expertise of human agents enables them to develop creative solutions to address unfamiliar challenges (Amabile, 1996). Further, prior studies demonstrate that when customers' questions are resolved in the selling process, customers are more likely make a purchase (Sabnis et al. 2013; Pennachin and Goertzel 2007). Thus, we expect that in a "horse race" between AI and human agents in performing the entire sales task (including lead generation and sales persuasion), AI agents are less effective than high-skilled human agents in sales persuasion, and thus the overall sales performance.

In this additional experimental group, 893 randomly selected customers were served by the AI chatbot alone. That is, the AI made outbound sales calls to customers to sell the product (credit cards), and performed both lead generation and sales persuasion without any human sales agents involved at any stage. The AI followed the same protocols and trainings as human agents of the firm, and made the calls during the same time slot as the four treatment groups reported in the main text. Randomization checks show that across experimental groups, all covariates, including customer age, gender, education, and number of credit cards owned, do not differ ($p > 0.58$).

The AI-alone group achieved a purchase rate of 0.021, which was similar to that achieved by bottom agents on their own (0.020) but half in magnitude as the purchase rate achieved by top agents on their own (0.037). The performance of the first-stage lead generation is the same across the three groups (which is consistent with Appendix 2), thus the variation of success of the second-stage sales persuasion closely traced the variation of the customer purchase rate. These results inform us that the AI chatbot on its own underperformed top-skilled sales agents on their own, not in lead generation but in sales persuasion. However, the AI chatbot on its own achieved a performance parity as bottom-skilled sales agents. While these insights are less relevant to the research question of the main text, we report them here for full transparency.