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Essays on artificial intelligence (AI) in management

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I hereby declare that this PhD dissertation is my original work

and it has been written by me in its entirety.

I have duly acknowledged all the sources of information

which have been used in this dissertation.

This PhD dissertation has also not been submitted for any degree

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周博文.

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Abstract

This dissertation comprises three essays that investigate the transformative potential of Artificial Intelligence (AI) in business.

Chapter 1 investigates the fundamental issue of how integrating AI within R&D activities influences a firm's market value. We developed an "AI Index" using patent data and textual analysis. Interestingly, empirical results indicate a negative correlation between AI integration and market value. However, this does not suggest that AI is an unviable avenue for exploration. Further analysis of the boundary conditions reveals that complementary assets are crucial for successful commercialisation, highlighting that while AI adoption is costly, these assets significantly enhance its market value.

In Chapter 2, my research has examined how firms have adapted their R&D activities to incorporate AI as a strategy to mitigate potential adversities arising from such conflicts. We leveraged the 2018 bans on Huawei as an exogenous shock and utilised a difference-in-differences model to evaluate the effects. The findings indicate that geopolitical conflicts have a positive impact on the adoption of AI in firms' R&D activities, as it enables them to preemptively address potential future restrictions.

Chapter 3 focuses on a more micro-level analysis, specifically on developers, examining how the advent of ChatGPT affects knowledge searching. Using Stack Overflow as a context, which separates question formulation from problem-solving, we conducted an exploratory-style empirical test. This study reveals that while AI-generated content technologies like ChatGPT provide more potential solutions, these do not necessarily translate into accepted solutions. Additionally, we discovered that the presence of AI increases the time required to evaluate these solutions. We also considered varying capabilities by examining search depth and scope, finding that AI benefits non-domain experts by reducing the learning curve costs.

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1. INTRODUCTION

This dissertation is composed of three essays that delve into the transformative impact of Artificial Intelligence (AI) on industries and business models, the effects of geopolitical conflicts on firms' R&D activities, and the influence of technological changes on knowledge search processes. AI is revolutionizing business operations in various ways, particularly through its engagement in innovation. It has become a focal point in the strategic competition between global superpowers, evidenced by a series of competitive actions and conflicts, such as the Huawei case. Against this backdrop, the dissertation addresses AI in management from different perspectives, exploring its potential, challenges, and implications for firms navigating this dynamic landscape.

The first essay explores AI's role as a general-purpose technology with the capacity to revolutionize industries and disrupt traditional business models. We propose that AI maximizes value when broadly applied across various technological domains, necessitating the integration of inter-domain cognitive skills and complementary assets. However, investments in AI do not guarantee immediate returns. Analyzing patent data from Chinese manufacturing firms, we find a negative correlation between the extent of AI-relatedness in a firm's innovation activities and its Tobin's Q. This negative effect is particularly pronounced when AI innovations are widely distributed throughout the firm's innovation portfolio. Interestingly, the negative impact is mitigated in larger firms or those experiencing rapid sales growth. Our study underscores the double-edged nature of AI in innovation and identifies conditions under which firms can benefit from AI-related innovations.

The second essay addresses the opportunities and challenges globalization presents for firms' survival and operations, focusing on the escalating Science and Technology (S&T) conflicts among global superpowers over the past two decades. While much scholarly attention has been given to the impact of geopolitical conflicts on firms' R&D activities, there is a dearth of research on how these conflicts specifically influence R&D strategies at the firm level. This study zeroes in on AI as a pivotal driver in the current technological era. Using the unexpected bans on Huawei by the US government as an exogenous shock, we employ a quasi-experimental design to examine how firms integrate AI into their R&D activities in response to geopolitical conflicts over S&T. Our empirical evidence suggests that geopolitical conflicts positively influence firms' AI integration within R&D. We further explore boundary conditions such as institutional heterogeneity and cognitive perception. Our findings indicate that the positive effects of geopolitical conflicts on AI integration in R&D are more pronounced in state-owned enterprises. Additionally, firms increase their AI integration in R&D following the imposition of bans on Huawei, perceiving these conflicts as threats to their technological sovereignty.

The third essay investigates how technological changes influence the specific components of knowledge search—namely, problem formulation and solution finding—from a problem-solving perspective. This study addresses a gap in the literature by examining the impact of AI-Generated Content (AIGC) technologies on the solution-finding process. Utilizing the introduction of ChatGPT in a quasi-experimental design, we analyze data from StackOverflow, a platform for crowdsourcing coding knowledge. Our findings reveal that post-ChatGPT, the likelihood of innovators obtaining responses increases, even after controlling for changes in problem formulation. However, this increase does not correspond to a higher likelihood of obtaining satisfactory solutions. Instead, it leads to prolonged durations for locating accepted solutions and extensive post-acceptance discussions. We also explore how the direction of innovators' knowledge search moderates these effects, attributing such heterogeneity to varying capabilities of solution evaluation—an often overlooked factor in the search literature.

2. THE DOUBLE-EDGED SWORD OF ARTIFICIAL INTELLIGENCE: EXPLORING THE LINK BETWEEN AI-RELATED INNOVATION AND FIRM VALUE

2.1 Introduction

Artificial intelligence (AI) technologies are becoming increasingly important in the business world. It is no doubt that these new technologies have the potential to transform various industries and disrupt traditional business models. Over the past decade, evidence has indicated a significant rise in AI-related activities including robotics shipment, AI start-ups, and AI-related innovations and applications (e.g., Brynjolfsson, Rock & Syverson, 2019; Furman & Seamans, 2019). The remarkable surge in the number of AI-related patents filed by firms over the past several years is particularly striking (Miric, Jia & Huang, 2023; WIPO, 2019). Correspondingly, researchers have increasingly turned their attention to exploring the impact of AI technologies on firm strategy and management (e.g., Felten, Raj & Seamans, 2021) and how these technologies reshape the source of competitive advantages of firms (e.g., Krakowski, Luger & Raisch, 2023).

AI technologies offer several advantages that can significantly enhance firm performance because of their capabilities in pattern recognition, prediction and automation (Agrawal, Gans & Goldfarb, 2017). For example, AI applications like AI-powered chatbots (Luo et al. 2019) or AI-based translation software (Brynjolfsson et al. 2019) enable more accurate predictions of human behaviours, thereby allowing firms to better serve their customers. Additionally, AI technologies can improve operational efficiency and decision making processes, as demonstrated in AI-augmented medical diagnoses (Lebovitz, Lifshitz-Assaf & Levina, 2022). Moreover, AI technologies facilitate R&D processes by enabling firms to explore the previously computational infeasible knowledge space. For instance, AI technologies can assist product developers in generating design alternative (Verganti, Vendraminelli & Iansiti, 2020) and scientists in exploring novel combinations of compounds in drug discovery (Fleming, 2018; Lou & Wu, 2021). Nevertheless there have been concerns and debates regarding the effects of AI on firm productivity and growth (Acemoglu, LeLarge & Restrepo, 2020; Babina et al., 2020; Brynjolfsson et al., 2019). Undoubtably, challenges, uncertainties and risks are associated with such emerging technologies. However, despite its importance and debate, our current understanding of the impact of AI-related innovation on firm performance remain very limited.

We suggest that one challenge in understanding the effect of AI technology on firm strategy and performance is its general-purpose technology (GPT) nature. Unlike other emerging technologies, AI distinguishes itself as a general-purpose technology (Goldfarb, Taska & Teodoridis, 2023). This GPT nature enables AI to be widely appliable across technological domains (Agrawal et al. 2017) and scale free (Brynjolfsson & McAfee, 2014, 2017). Given its potential as a new source of competitive advantage (Krakowski et al., 2023), maximizing the value of AI technology would entail effective application across multiple domains. However, the realization of this value also requires substantial domain-specific cognitive capabilities, experience, and complementary assets that are not scale free and difficult to transfer across domains. As a result of this inherent tension, we propose that the value realization of AI technology would be significantly constrained.

To investigate this mechanism, this study examines the impact of AI-related innovation on firm value in a sample of Chinese manufacturing companies. Unlike most of the previous literature that have focused on the AI-using scenarios (e.g., intelligent chatbot or AI-based diagnosis), our focus is on AI-inventing firms that integrate AI technologies in their innovations. We analysed the degree of relatedness of a firm's patent portfolio to AI technologies and our finding indicates a negative relationship between the firm’s degree of

AI-relatedness in innovation and the firm's Tobin's Q, especially if the AI technologies are widely distributed across the firm’s patent portfolio. Nevertheless, this negative effect can be mitigated if the firm is large or experiencing fast growth. The results of our study reveal the double-edged nature of AI technologies in innovation and identify conditions that may help firms benefit from AI-related innovation.

2.2 Theory and Hypotheses Development

Patents are often regarded as an important indicator of a firm's innovation activities, and a rich literature has found that patents are positively associated with firm performance (Hall, et al. 2005). Patented innovation can not only commercialize through new products but also provide a degree of market exclusivity, enabling firms to charge higher prices and capture more value from their innovative output. The stock of patents represents a valuable collection of knowledge assets (e.g., McGahan & Silverman, 2006; Qian, et al., 2017). The knowledge assets developed through a firm's innovation activities are specific to that firm, making them difficult to imitate, and thereby reducing the dampening effect of competition and increasing returns to innovation (Helfat, 1994). Similarly, AI-related patents that incorporate AI technologies in other technologies can signal a firm's capability and first-mover advantage in the emerging technological areas such as AI, thereby attracting investors' attention, and becoming the driver for competitive advantage of the firm.

Artificial intelligence is a new general-purpose technology (GPT) with the potential to revolutionize many industries by stimulating the development of new manufacturing technologies and products. The applications of AI-related technologies, such as machine learning, autonomous vehicles, image and nature language analysis, robots and machine augmentation, are numerous and can be applied in various fields. By recombining AI with other technologies, firms can discover new opportunities for innovation and product development (Agrawal et al., 2019). For instance, machine learning algorithm can be incorporated in manufacturing equipment to enhance the manufacturing process by automatically learning production patterns from data, resulting in lower error rates compared to human-performed actions (Agrawal et al. 2017, Brynjolfsson & Mitchell, 2017). In particular, Goldfarb et al (2023) used job posting data to demonstrate that out of 21 different emerging technologies, machine learning is most likely to be a GPT due to its extensive economic impact. Some scholars believed that AI has the potential to be the most important GPT of our era (Brynjolfsson & McAfee, 2017).

However, what has been less studied is the adverse effect that AI may have on firm productivity and performance. The investment in AI technologies and AI-related innovations may not always generate productivity gains and positive returns immediately. We content that the nature of AI technologies as GPT is a double-edged sword. While the maximization of value of AI technologies relies on their extensive application across various technological domains, firms may face challenges in acquiring the necessary human cognitive skills and complementary assets that are often domain-specific and difficult to transfer across different domains.

While AI technologies hold great promise, they may not be able to fully replace the experience of human workers in many production processes (Agrawal et al, 2017). The integration of AI technologies that do not align well with the existing workforce and technologies can lead to substantial adjustment cost. Rich experience and deep domain knowledge accumulated through human cognitive capabilities are indispensable for the effective application of AI technologies in any technological domain. In AI-related innovation or application that is based on deep learning, human cognitive capabilities, experience and judgement is particularly important simply because we still have a very limited understanding of why deep learning works (Ahmed & Wahed, 2020; Leboovitz et al., 2022). This type of work is heavily reliant on people who have accumulated related expertise through formal training (e.g., PhD) or years of applied work in related technological domains (Ahmed & Wahed, 2020). Lou and Wu's (2021) study in drug discovery suggests that to fully unleash the potential of AI requires the firm to match the human talents with AI skills that can combine effectively AI technologies and medical knowledge. Those firms with employees who individually possess both AI and domain knowledge are more likely to have valuable drug discovery.

According to the resource-based view of firm, for an innovation or knowledge asset to contribute to a firm's competitive advantage, it needs to be specific to the firm's unique organizational structure so as be rare and inimitable (Barney, 1991; Helfat & Peteraf, 2015). As a result, advantage-generating resources, such as humans' domain-specific cognitive capabilities, tend to have low fungibility (i.e., not scale-free) and could not be easily applied to unrelated domains (Helfat & Peteraf, 2015). This creates a fundamental tension between the scale-free and cross-domain nature of general-purpose AI technologies (e.g. Brynjolfsson & McAfee, 2014, 2017), and the domain-specific cognitive capabilities and knowledge of humans. While AI technologies can be applied extensively cross domains, the effective application requires substantial cross-domain learning for humans, resulting in significant economics costs that can quickly outweigh the potential benefits. Yet the firm-specific domain-specific human cognitive capabilities are becoming increasingly important for AI-related innovation because competing firms with similar technologies can easily imitate by applying AI technologies in their technologies if no domain-specific human skills involved.

In addition, the successful commercialization of AI innovations often requires complementary innovations and assets (Pisano, 1994; Teece, 1986, 2018), which may not keep pace with the development of AI technology. This may lead to a gap between the potential of AI innovations and their actual commercial success due to the insufficient development of complementary assets. As Teece (1986) pointed out, being the innovator is not necessarily advantageous because the firms that can benefit from innovation would be those who can exploit the existing complementary assets. Complementary assets include market-related knowledge, brand reputation, distribution channels, customer contacts and access to partners (Rothaermel, 2001, Tripsas, 1997). Such complementary assets rely on a firm's experience that accumulated through past market participation and the human capital with specialized knowledge in commercialization of new technologies (Teece, 1986). The success rate of commercialization of innovation is more likely to increase with firms' experience in product-market domains (Nerkar & Roberts, 2004). Additionally, besides the market-related complementary assets, AI technologies relying on machine learning also require specialized equipment like big dataset and compute power (Ahmed & Wahed, 2020). Increased computer power is complementary to algorithms and big data, but also demands significant investment in relevant technologies such as GPUs or compute cloud (Thompson & Spanuth, 2018).

Finally, it takes time for firms to develop firm-specific knowledge assets and capture the rent generated by the innovation associated with AI technologies that are emerging technologies with high uncertainty. As the emerging technology, AI technologies progress very fast, and impose substantial technological and market uncertainty for firms (e.g., Lou & Wu, 2021), which make it even crucial to have domain-specific capabilities and knowledge. Although it is undeniable that every AI-related innovation has the potential to create value for a firm, we suggest that investing in this type of innovation may be more uncertain and challenging in terms of generating sufficient and immediate positive returns compared to other innovations. Not only are domain-specific human skills difficult to harness, but the inter-domain human skills are even rarer and more difficult. As such, in this study, we propose that after controlling for the total innovation stock, the degree of AI-relatedness in a firm's innovation portfolio may negatively affect firm value. The degree of AI-relatedness indicates the allocation of firm resources in AI-related innovation compared to other innovation.

Hypothesis 1: The degree of a firm's patenting in the AI domain (i.e., AI-relatedness) is on average negatively associated with the firm value.

Following hypothesis 1, we also predict that those firms with innovation portfolios that apply AI technologies in broader domains will face stronger challenges in realizing the commercial value of AI-related innovation. As we analyzed above, to have AI technologies applied to any domain can be difficult because of the necessary domain-specific cognitive capability. To spread innovation efforts of AI technologies in multiple domains requires additional strong inter-domain capabilities for the integration of knowledge. Furthermore, to apply AI technologies in multiple domains will make the firm face competitors with AI-related innovation in multiple domains.

Hypothesis 2: The negative association between the AI-relatedness in innovation and firm value becomes more negative when AI technologies are applied across broader technological domains.

We further argue that the negative association in hypothesis 1 may be conditional on a firm's access to complementary assets. Given that the successful commercialization of AI-related innovations often requires complementary assets and complementary innovation infrastructure (Pisano, 1994; Teece, 2018), firms with complementary assets are better positioned to generate new product development and commercial opportunities for such innovation. Large firms that are endowed with extensive resources are less likely to be negatively affected by the increased need for specialized equipment (e.g., dataset, compute). Large firms are more likely to have a greater accumulation of big data that facilitates AI technology development. It is not surprising to observe that elite universities (Ahmed

&Wahed, 2020) or large firms (Miric et al. 2023) have better advantage than average universities in generating AI-related innovation. When the AI talents become increasingly scarce resource, larger firms are more likely to afford to recruit and retain these technological talents (Ahmed & Wahed, 2020).

Similarly for the firms with fast market growth. Fast growth indicates the firm has commercial capabilities that enable the firm to develop appropriate new product out of new technologies and put them through the market successfully. For example, Audretsch (1995) found that firms with fast growth can adjust fast and develop viable products and therefore have high chance of survival in a highly innovative environments. Recently, Babina et al (2020) found that AI investments are related to firms' expansion across geographic markets and creation of new products. In turn fast growing firms gain confidence and provide more resources to AI-related innovations. As such, we predict the following.

Hypothesis 3: The negative association between the degree of AI-relatedness in innovation and firm value becomes less negative when the firm is larger.

Hypothesis 4: The negative association between the degree of AI-relatedness in innovation and firm value becomes less negative when the firm is having a fast growth.

2.3 Databases and Sample

We constructed a sample of Chinese manufacturing firms listed in Chinese stock market in 2014 and follow their patent activities till 2020. The manufacturing industry in China exhibits a high level of intensity in its R&D activities, providing an opportunity to observe their efforts in the field of AI. Recent studies have shown a growing trend of Chinese manufacturing firms adopting AI technologies in order to enhance their productivity and performance (Luo, 2021). At the same time, we choose 2014 as several important events took place in that year that marked the beginning of a new era for the widespread adoption of AI by businesses. For instance, Google acquired DeepMind in 2014, which signalled a major push by the company to invest in AI (Gershgorn, 2018). Additionally, the number of AI-related patents filed in 2014 increased by 20% from the previous year (WIPO, 2015). The firm level data were collected from the widely used China Stock Market and Accounting Research database (CSMAR), and the patent level data were collected from China Intellectual Property Administration (CNIPA). The final sample is an unbalanced panel data set that is composed of 1,159 firms and 7,796 firm-year observations.

2.3.1 Variables

Dependent variable. As noted by prior research in strategic management and innovation, Tobin's Q is a widely used measure of firm performance and is particularly suitable for capturing market valuation compared to accounting-based measures such as ROA or ROE. One reason for this is that accounting-based measures may be subject to managerial manipulation, leading to biased evaluations of firm performance (e.g., Miller et al., 2015; Shleifer & Vishny, 1997). Another reason is that Tobin's Q is a forward-looking measure that effectively reflects investor sentiment towards a firm's future prospects (›Qian et al., 2017). This makes Tobin's Q a suitable measure for evaluating how investors evaluate a firm's investment in AI technologies and whether such investments lead to an increase in firm value. The variable *Tobin's Q* was measured by dividing the market value of a firm’s equity by the book value of its total assets with natural logarithm.

Independent variable. AI-relatedness. Recent developments have emerged in categorizing innovations related to AI technologies (Miric, et al., 2023). Miric, Jia, and Huang (2023) discuss the importance of accurately categorizing innovations related to AI technologies, highlighting the challenges associated with such categorization. In this study, we adopt a new methodology proposed by Babina et al. (2020) to proxy human-talent investment in the AI domain (Babina et al., 2020; Boudreau et al., 2021). These scholars identified three core terms, Machine Learning (ML), Natural Language Processing (NLP), and Computer Vision (CV), that have minimal ambiguity in the classification with AI technologies. They then constructed a matrix for each job skills description to capture the relatedness of that skill to the three core AI terms, with higher relatedness indicating greater relevance of human capital to AI technologies.

Compared to AI-based (e.g., supervised machine learning) methods (Miric et al., 2023) and dictionary-based (e.g., keyword-based) method for classification, the core-terms-based method has two distinct advantages. First, AI-based methods and keyword-based identification strategies rely heavily on the accuracy and credibility of the core set or keyword list selected by researchers. Second, AI-based methods require a powerful computing platform and AI-specific knowledge. A recent study by Chen et al. (2021) used Babina et al's methodology to measure AI-related innovation in the semiconductor industry and found that firms investing more in AI related human-talent were more likely to have better patent outcomes. In this study, we utilize the core-terms-based methodology to identify AI-related patenting activities at the firm level through analysing patent filings (*AI-relatedness*). We adopt the same three core terms (i.e., the Chinese terms for Machine Learning, Natural Language Processing, and Computer Vision) as used by Babina et al. (2020).

We then calculate the relatedness of each unique word/term included in patent abstracts with these core terms, in order to identify AI-related patents filed by the firms. Specifically, for each unique word j, we calculate the coefficient W_j,

$$W_j = \frac{\#\ of\ patents\ with\ word\ j\ and\ any\ core\ word\ in\ patent\ abstract}{\#\ of\ patents\ with\ word_j} \quad (1)$$

The score of W_j ranges between 0 and 1. The value of 1 indicates that the unique word j is always associated with the core AI terms, indicating its importance to the AI-related innovation activities. The value of 0 indicates that the word j never appears in AI-related patents, indicating that this word has no relation with AI technologies. (The word list is attached in the appendix A). We then aggregate the relatedness at word level to patent level by averaging the W_j score of all unique word present in a patent's abstract, which is labeled as P_i.

By implementing our innovative identification method, which relies on analyzing patent abstracts, we have successfully captured the degree of AI-relatedness at the firm level. Our approach involves examining both the top and bottom 25% of patent abstracts (see the appendix 1), providing us with representative examples for analysis. The top 25% of patent abstracts serve as an excellent indicator of cutting-edge advancements in artificial intelligence, showcasing the firms' development of sophisticated AI algorithms, machine learning models, and neural networks. Conversely, the bottom 25% of patent abstracts exhibit relatively low relatedness to the AI domain. This comprehensive methodology ensures that our identification method is efficient and valid for assessing the extent of a firm's connection to AI techniques. By considering the entire spectrum of patent abstracts, we can confidently claim that our approach accurately represents the level of AI-relatedness within firms, making it a reliable tool for understanding their AI adoption and innovation. At the word level, appendix shows the top 10 keywords that are closely related to the three core terms. Comparing these terms with those reported in previous studies (e.g., Miric et al. 2023), we can see that the terms used in Chinese patents are quite different from previous studies using USPTO patent data.

Finally, based on the calculation of P_i, we create the variable *AI-relatedness* by averaging the score of relatedness to AI-technique at t the patent level (P_i) across all patent fields filed by the firm in the particular year. The higher value of AI-relatedness indicates the related higher level of investment in AI domains.

Moderating variables. Dispersion of AI-relatedness (Dispersion). Dispersion is defined as the extent of penetration of *AI-relatedness* in focal firm's R&D activities (i.e., one minus the concentration of AI technique adoption). Drawing from the calculation of Herfindahl-Hirschman index (HHI), we measure the score of evenness of AI-technique adoption by the following specification, where i refers to all patents filed by the firm k in the particular year. The higher value indicates the deeper penetration of AI techniques for focal firm's R&D activities.

$$Dispersion_{i\in k} = 1 - \sum_{i=1}^{i}\left(\frac{P_i}{\sum_{i=1}^{i} P_i}\right)^2 \quad (2)$$

Firm size. Following prior literature, we calculate the firm size by natural logarithm of total assets.

Growth. Growth is calculated change in sales as $(sales_t - sales_{t-1})/sales_{t-1}$, where $sales_t$ represents focal firm's size in any given year t and $sales_{t-1}$ represents firm in the previous year.

Control variable. The analysis controlled for several factors at the firm-, patent-level factors that may affect a firm's financial performance and the extent of AI-relatedness. At the firm level, we controlled debt ratio because higher debt ratio is always associated the stability and possible risk faced by the firms. Debt ratio was measured by the ratio of each firm's long-term debt to its total assets. Additionally, we also control the sales, which is associated with firm's market value and performance (Pauwels, 2004). Next, we include the natural logarithm of financial slack as the control variable (O'brien, 2003). Then, we controlled the ownership type via the dummy variable to indicate whether the firm is SOE or not because prior research has found that SOE is associated with the heterogeneity of resource accessibility and firm performance (Zheng et al., 2015; Greve & Zhang, 2017).

At the patent level, we include the number of patent as the control variable accounting for the heterogenous capabilities to converting R&D activities into patent as the output. The number of patent is measured by the total number of patent applications in last year (Hall, et al. 2005; Ceccagnoli, 2009). Additional, given the limited resources and attention, research has unraveled that the interplay and trade-off between firm's exploration and exploitation is associated with firm's market value and performance. Thus, we control the proportion of exploration by including the ratio of firm's exploration in new IPC-subclasses to its total number of IPC-subclass filed by the firm (Uotila et al.,2009; Nerkar & Roberts, 2004).

2.3.2 Estimation model

In this research, we employ panel data Ordinary leas square (OLS) estimation with firm- and year- fixed effect. The main explanatory variable was AI-relatedness, dispersion, firm size and growth. Thus, if γ is defined as firm's market value in terms of Tobin's Q, the model specification is

$$\gamma_{t+1} = \beta_1 Ai - lization_t + \beta_2 Dispersion_t + \beta_3 firm\ size_t + \beta_4 growth + \beta_5 Ai - lization_t \times Dispersion_t + \beta_6 Ai - lization \times firm\_size_t + \beta_6 Ai - lization\ _t \times growth + control_t + \varepsilon_t \quad (3)$$

The main focus of our interest in terms of hypothesis 1 was β_1, representing the relationship between AI-relatedness at time t and market value at $t+1$. To test for any moderating effects of dispersion, firm size and growth, equation 3 also incorporates the interaction of dispersion and AI-relatedness, interaction of firm size and AI-relatedness, and interaction of growth and AI-relatedness respectively.

We select this methodology to avoid obtaining biased estimates due to the potential endogeneity of the regressors and the unobservable heterogeneity problem. Endogeneity is likely to appear when the explanatory variable is estimated simultaneously with the dependent variable, such that AI-relatedness and firm size may be influenced by the firm's past market value. Also, the firm with higher market value would be more likely to explore and invest in AI-domain, which results in the rise of endogeneity issue. Additionally, there exits unobserved firm heterogeneity that my affect the relationship between firm's R&D activities in AI domain and its market value. The biased estimation may occur if it failed to solve or eliminate such unobserved firm heterogeneity.

Given the possibility of biased estimation, we address these issues by following ways. We run the regression model by including a lagged dependent variable to avoid the issue of simultaneous evaluation of explanatory variable and dependent variable. In our case, we adopt the lagged market with natural logarithm as the dependent variable in the OLS model. Moreover, we include the firm fixed effect to account for the firm level heterogeneity. Likewise, the time-related heterogeneity was modeled as time fixed effect.

2.4 Results

Table 1 presented descriptive statistics and contains the correlation for our sample. In line with previous literature, the mean value of the natural logged Tobin's Q was 1.089. Firm's market value (natural logged Tobin's Q) was found to be significantly and negatively related to debt ratio, number of patent, firm size, financial slack and state-owned business. Likewise, at the patent level, firm's market value is significantly and negatively correlated to number of patent and exploration.

Table 2 presented the results of OLS regression for the hypotheses with natural logged Tobin's Q as the dependent variable. In model (1), we included only control variables with firm and year fixed effect. Tobin's Q was found to be significantly positively correlated to dispersion, sales and financial slack. In addition, firm with more patents tends to generate lower market value.

Model (2) presented results with Ai-relatedness measurement added. Consistent with Hypothesis 1, the coefficient of AI-relatedness was negative and significant ($\beta = -0.055, p < 0.1$). Therefore, our hypothesis is supported. Model 3 to 5 shows the results of boundary condition for hypothesis 1. To test hypothesis 2, we introduce the interaction term between AI-relatedness and Dispersion. The coefficient of the interactive term was negative and significant ($\beta = -0.088, p < 0.1$), providing support for our hypothesis 2. Likewise, we examined the moderating effect that negative effect of AI-relatedness on firm's market value will be weakened if the firm has larger firm size (hypothesis 3). The coefficient of the interaction term is positive and significant ($\beta = 0.133, p < 0.001$), providing support for our hypothesis 3. To test hypothesis 4, we include the interaction term between AI-relatedness and growth into the OLS model. The coefficient of the interaction term is positive and significant, ($\beta = 0.075, p < 0.1$), which indicates that the negative effect of AI-relatedness on market value is less salient for the firm at the stage of rapid growth. Therefore, our hypothesis 4 is supported.

2.5 Robustness Checks

Overall, we found supporting results for all our hypotheses. To check the robustness of our findings, an alternative measurement was employed in addition to the primary measurement in the test. The results of the alternative measurement remain identical to the results in Table 2. Next, we tested several additional variables as control variables such as quality of patent, innovation breadth and financial leverage, and none of these variables has much impact on the main results.

We also tested industry-related variables such as average AI-related investment within the industry. These variables did not provide any additional information to the fixed-two-digit industry effects. Lastly, we rerun standard errors clustered for each firm to account for firm-specific unobserved factors. The result is identical. Moreover, we conducted the firm random-effect Tobit model to control for the unobserved firm factors and the results are consistent. To strengthen the robustness and exclude the possible U-shaped relationship between AI-relatedness and firm's market value, we also run the OLS model by incorporating squared term of AI-*relatedness* into the OLS model. The coefficient for the squared term is not significant, which indicate that there does not have the non-linear relationship between AI-relatedness and firm performance.

Although we have adopted the lagged variables in the estimation, which has accounted for the reversed causality, our results may still suffer from endogeneity issue. The endogeneity is likely when explanatory variables are evaluated simultaneously with the dependent variable, such that a firm's investment in AI-technique and market value may be affect by the firm's previous performance. Additionally, it is possible that firm with better market value would be more likely to invest in Ai-related technique to generate more profits in the future. Finally, there may exist the unobserved firm heterogeneity that may affect the relationship between AI-relatedness and firm's market value. These endogeneity issues would lead to the biased estimation.

To address the endogeneity issue, we treat the AI-related investment as the endogenous variable and its interaction with moderator variables also endogenous in the estimation (moderator should do the iv test). We use the STEM graduates as the instrumental variables (i.e., graduates in Science, Technologies, Engineering and Mathematics) because it can provide the rare human talents to facilitate AI-relatedness but not necessarily correlated to firm's market value. The results using this approach generated supporting evidence to our hypotheses as well.

2.6 Discussion and Implication

To the best of our knowledge, our study represents one of the first attempts to examine AI-related innovation in China context, using patent data. In particular, we employ a novel approach for identifying AI-related innovation that is more flexible and accessible for researchers. The findings indicate that a high proportion of AI-related innovation in a firm's innovation portfolio may not yield immediate positive returns, particularly when the firm adopts AI technologies across patents in broader technological domains. This situation can pose an even greater challenge for smaller firms and firms with stagnant growth.

While our findings of negative expected returns from investing in AI-related innovation may seem counterintuitive, we believe that our study can offer a unique perspective on how to approach the investment in these new technologies. Our study highlights the challenges and uncertainties that firms may face when investing in this type of innovation. By considering these factors, firms can make more informed decisions about how to best leverage AI innovation to create value and maintain a competitive advantage.

Investing in AI-related innovation may still be too early for some firms, at least in our sample firms in China, as the first-mover advantage may not necessarily lead to a payoff (e.g., Teece, 1986). In the case of AI-related innovation, the technology is still evolving and improving rapidly, and it may take time for firms to fully understand and leverage its capabilities to combine it effectively with other technologies. Rushing to invest in AI-related innovation without a clear strategy or understanding of the technology could result in wasted resources and missed opportunities.

It is not surprising that this study confirms the idea that AI technologies and AI-related innovations, just like any new or emerging technologies, can have both advantages and disadvantages. In particular, this study makes contribution to innovation studies and strategic management studies by pointing out the duality of the nature of AI as a general-purpose technology. To recap our key argument, AI technology has to be broadly applied across technological domains if a firm wants to maximize its potential value. However, this approach poses challenges for the firm due to the scarcity of both domain-specific human cognitive capabilities and inter-domain capabilities that are indispensable for integrating AI technologies into innovations and transforming them into advantage-generating resources. As such, lacking an understanding of the benefit and limitations of AI could lead to misallocation of value resources to the types of projects where AI provide minimal benefits or AI's benefit potential could not be fully realized.

We concur that the successful commercialization of AI-related innovation requires the development of a larger ecosystem that can provide complementary assets (Teece, 2018). This ecosystem involves partnerships with suppliers, customers, digital platforms, and even competitors. Moreover, AI technology is a disruptive innovation that requires significant organizational changes to successfully implement (Bower & Christensen, 1995). The scale of organizational change needed for AI-related innovation can be extensive and requires significant resources, both in terms of time and money. This can create challenges for firms that are not prepared to undertake such large-scale changes, and may result in a slower return from investing into such innovation.

Furthermore, being the first-mover in AI-related innovation may not necessarily be advantageous as competitors may quickly catch up. However, our findings suggest for the future research that the rent generation of AI-related knowledge may benefit from the involvement of competitors, as they may generate complementary innovation and network effect that can enhance the overall value of the technology (Acemoglu et al. 2020; Babina et al. 2020)). It is possible that AI-related innovation may be best described by the co-opetition scenario, where competitors become collaborators in developing and using the new AI-related innovation (Nalebuff et al., 1996). AI technology is complex and multifaceted, and it may require the involvement of multiple firms to eliminate the technological uncertainty and to fully realize its potential. By collaborating with competitors, firms can reduce the risks and costs associated with innovation, while simultaneously expanding their knowledge and capabilities in the AI space. To further explore the effect of competing firms and how AI technologies diffuse through competing or collaborating firms could be a fruitful avenue for future research. Finally, our study confirms the idea that AI technology and AI-related innovation may benefit larger firms more than smaller firms, and there may be a Matthew effect at play (Merton, 1968).

This is because the development of AI technologies requires significant resources, capabilities, and particularly data, which larger firms are more likely to possess. As a result, larger firms may have a competitive advantage in developing and utilizing AI innovation, which may increase their market power and further widen the gap between them and smaller firms. Our finding is not inconsistent with recent studies. For example, Miric et al (2023) found that large technology companies were featured prominently as holders of AI patents in the US. Acemoglu et al (2020) found that larger firms are more likely to adopt AI technologies in robots and automation. Ahmed and Wahed (2020) cautioned against the de-democratization of AI technologies as larger firms gain a growing advantage over small and medium-sized firms. While AI innovation has the potential to benefit society as a whole, the current distribution of resources and capabilities means that its benefits are primarily accruing to larger firms, and this may have long-term implications for the competitiveness and dynamism of the economy (Brynjolfsson & McAfee, 2017).

Nevertheless, our study also reveals that fast growing firms, not necessarily the large firms, can benefit from the AI-related innovation. This highlights the significance of human skills and management capabilities that enable successful market expansion and growth can be equally important for dealing with uncertain and fast-paced AI technologies. Our study only scratches the surface of this phenomenon. Future studies are encouraged to delve deeper and unravel the underlying capabilities and mechanism that truly support the success of AI-related innovation.

2.7 References

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2.8 Tables

Table 1. Descriptive Analysis

	Mean	s d	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Market value (1)	1.089	0.354	0.556	4.851	1										
AI-relatedness (2)	0.128	0.152	0.000	3.209	0.011	1									
Dispersion (3)	0.827	0.261	0.000	1.000	0.001	-0.157***	1								
No of patent (4)	1.895	1.586	0.000	9.201	-0.102***	0.432***	0.230***	1							
Exploration (5)	0.231	0.230	0.000	0.693	-0.054***	0.063***	-0.028**	0.050***	1						
Debt ratio (6)	0.065	0.174	-1.983	11.332	-0.112***	-0.011	0.023**	0.044***	-0.022*	1					
Firm size (7)	0.511	0.543	0.004	4.453	-0.356***	0.110***	0.115***	0.383***	0.029**	0.135***	1				
Growth (8)	0.175	1.002	-0.991	55.044	-0.013	-0.007	0.014	-0.019	0.011	0.007	0.019	1			
Sales (9)	0.082	0.300	0.000	9.020	-0.159***	0.093***	0.072***	0.275***	0.004	0.044***	0.664***	-0.005	1		
Financial Slack (10)	1.102	0.490	0.111	4.977	0.331***	0.085***	-0.044***	-0.071***	-0.021*	-0.132***	-0.336***	-0.008	-0.154***	1	
State owned business (11)	0.329	0.470	0.000	1.000	-0.149***	0.015	0.066***	0.113***	0.005	0.082***	0.315***	-0.028**	0.181***	-0.224***	1

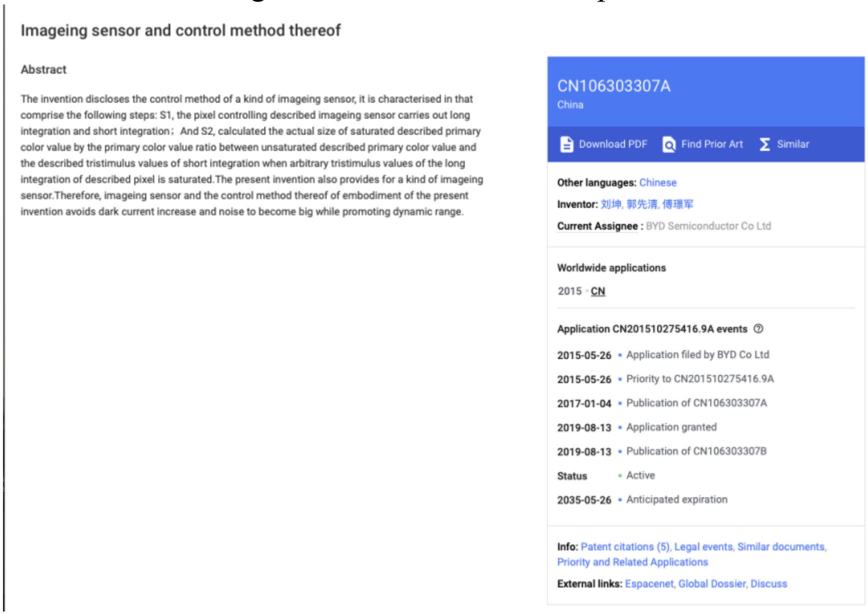
Table 2. Results

VARIABLES	Model 1	Model 2	Model 3	Model 4	Model 5
AI- relatedness		-0.055*	-0.012	-0.123***	-0.069**
		(0.028)	(0.042)	(0.039)	(0.027)
AI-relatedness X firm size				0.133***	
				(0.044)	
AI-relatedness X growth					0.075*
					(0.037)
AI-relatedness X dispersion			-0.088*		
			(0.05)		
Dispersion	0.013**	0.005	0.013	0.004	0.005
	(0.006)	(0.007)	(0.008)	(0.007)	(0.007)
No of patent	-0.006***	-0.004	-0.001	-0.003	-0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Exploration	-0.012	-0.012	-0.012	-0.012	-0.012
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Debt ratio	-0.036	-0.036	-0.036	-0.036	-0.036
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Firm size	-0.035	-0.035	-0.035	-0.054	-0.035
	(0.044)	(0.044)	(0.044)	(0.045)	(0.043)
Growth	-0.003	-0.003	-0.003	-0.003	-0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Sales	0.263***	0.265***	0.267***	0.234***	0.263***
	(0.069)	(0.069)	(0.069)	(0.064)	(0.068)
Financial Slack	0.018*	0.017*	0.017*	0.016*	0.018*
	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)
State owned business	-0.035	-0.034	-0.035	-0.032	-0.033
	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)
Constant	1.084***	1.093***	1.085***	1.105***	1.093***
	(0.031)	(0.031)	(0.031)	(0.030)	(0.031)
Firm fixed effects	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes
Observations	7796	7796	7796	7796	7796
R-squared	0.766	0.766	0.766	0.766	0.766

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2.9 Figures

Figure 1. Patent which has top 25% score of AI-relatedness



Imageing sensor and control method thereof

Abstract

The invention discloses the control method of a kind of imageing sensor, it is characterised in that comprise the following steps: S1, the pixel controlling described imageing sensor carries out long integration and short integration； And S2, calculated the actual size of saturated described primary color value by the primary color value ratio between unsaturated described primary color value and the described tristimulus values of short integration when arbitrary tristimulus values of the long integration of described pixel is saturated.The present invention also provides for a kind of imageing sensor.Therefore, imageing sensor and the control method thereof of embodiment of the present invention avoids dark current increase and noise to become big while promoting dynamic range.

CN106303307A
China

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Other languages: Chinese
Inventor: 刘坤, 郭先清, 傅璟军
Current Assignee : BYD Semiconductor Co Ltd

Worldwide applications
2015 · CN

Application CN201510275416.9A events

2015-05-26	Application filed by BYD Co Ltd
2015-05-26	Priority to CN201510275416.9A
2017-01-04	Publication of CN106303307A
2019-08-13	Application granted
2019-08-13	Publication of CN106303307B
Status	Active
2035-05-26	Anticipated expiration

Info: Patent citations (5), Legal events, Similar documents, Priority and Related Applications
External links: Espacenet, Global Dossier, Discuss

Figure 2. Patent which has bottom 25% score of AI-relatedness

A kind of shell and tube reactor suitable for olefin oxidation

Abstract

The invention discloses a kind of shell and tube reactor suitable for olefin oxidation, including housing, first end socket and the second end socket at the housing both ends are located at, and more reaction tubes being arranged in the housing； The more reaction tubes are located at one end closing of the first end socket, are connected positioned at one end of the second end socket with second end socket； Tapping sleeve is equipped with the reaction tube, the tapping sleeve includes feed zone and perforate section, the blind end of the feed zone through the reaction tube is connected with first end socket, and the length direction of perforate section along the reaction tube is set in the reaction tube and side wall is equipped with multiple apertures.Material is sent into catalyst bed by the material casing of perforate, no longer form the concentration gradient of material, eliminate catalyst bed hot spot, there is no concentration gradient problem in terms of mass transfer, so there is no the high situation of material concentration to trigger thermal accumlation to pass the problem of not going out, so as to solve the problems, such as two aspects of mass transfer and heat transfer.

Classifications

B01J8/06 Chemical or physical processes in general, conducted in the presence of fluids and solid particles; Apparatus for such processes with stationary particles, e.g. in fixed beds in tube reactors; the solid particles being arranged in tubes

View 7 more classifications

CN107952400A
China

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Other languages: Chinese
Inventor: 万毅, 崔娇英, 尹育, 曹传宗, 孙康, 胡进, 易光铨, 于海彬, 初乃波, 黎源, 华卫琦
Current Assignee : Wanhua Chemical Group Co Ltd

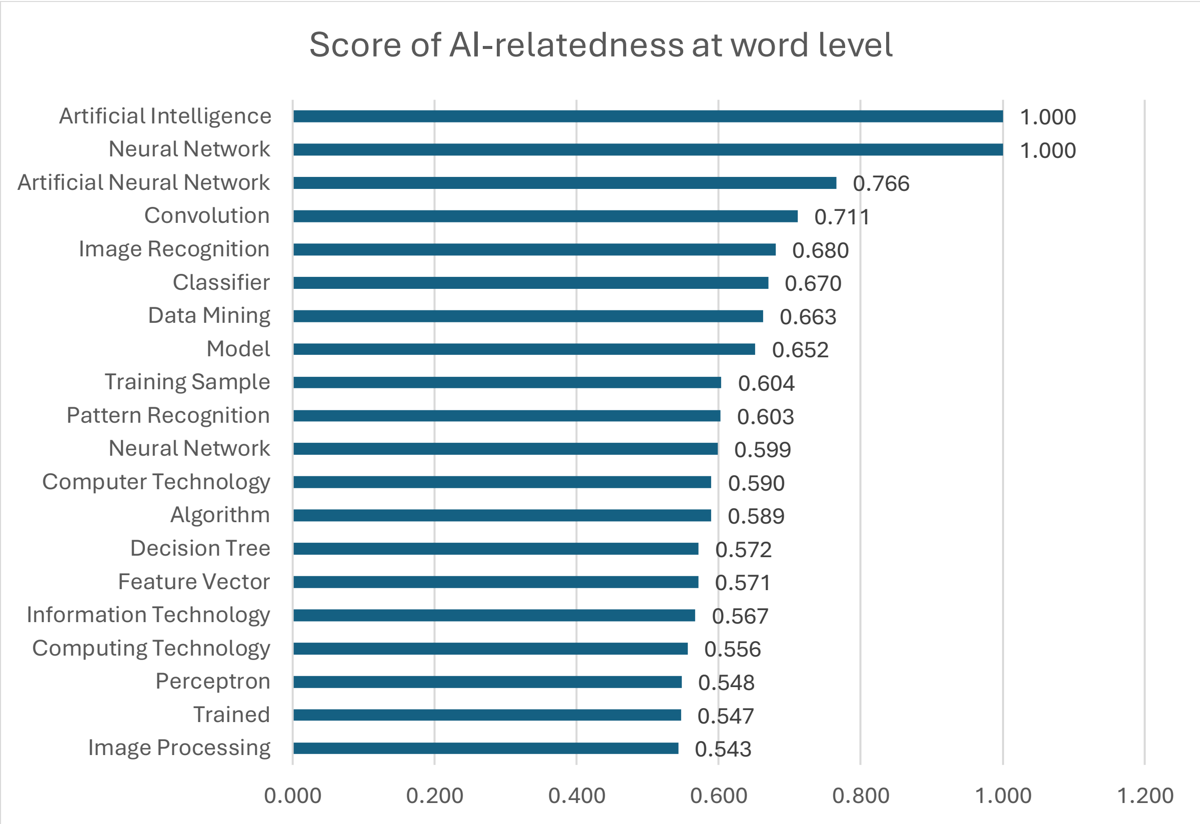
Worldwide applications
2017 · CN

Application CN201711218997.8A events

2017-11-28	Application filed by Wanhua Chemical Group Co Ltd
2017-11-28	Priority to CN201711218997.8A
2018-04-24	Publication of CN107952400A
2019-12-13	Application granted
2019-12-13	Publication of CN107952400B
Status	Active
2037-11-28	Anticipated expiration

Info: Patent citations (9), Non-patent citations (2), Cited by (1), Legal events, Similar documents, Priority and Related Applications
External links: Espacenet, Global Dossier, Discuss

Figure 3. Score of AI-relatedness at word level



3. GEOPOLITICAL CONFLICTS AND ARTIFICIAL INTELLIGENCE (AI): EVIDENCE FROM BANS ON HUAWEI

3.1 Introduction

In recent decades, escalating challenges to globalization, such as geopolitical tensions, environmental concerns, rising nationalism, technological disruption, supply chain vulnerabilities, and terrorism, have induced a surge in conflicts and a noticeable shift towards deglobalization. These challenges are exemplified by events like the Brexit referendum, the trade war between China and the United States, and the U.S. implementation of anti-dumping policies targeting Chinese exports, signaling a reevaluation of international relationships and economic strategies. Although there has been long interest to understand the consequence of geopolitical conflicts (e.g., Jacob et al., 2022, Han et al., 2024), there is limited research that explores the strategic reaction toward the geopolitics conflicts at the firm level.

Science and Technology (S&T) have become the central arena for superpower rivalry in the era of globalization, highlighting the deeply politicized nature of these fields (Beugelsdijk and Luo, 2024). Scholars have extensively explored the influence of geopolitical conflicts on corporate research and development strategies, focusing particularly on the impact on patent quality and quantity. For example, Huang et al. (2024) demonstrated that anti-dumping policies significantly boost both the number and quality of patent applications as companies seek to preempt future challenges. Additionally, Han et al. (2024) developed an indicator for technological decoupling at the patent level, revealing that U.S. sanctions on Chinese high-tech enterprises promote such decoupling from the Chinese perspective. However, this body of research overlooks the direct effects of tariffs on firms, missing a crucial chance to analyze strategic responses at the company level.

This study addresses these gaps by analyzing the specific actions taken by the U.S. government against Huawei in 2018, which was perceived as a national security threat. It examines the repercussions on Huawei's peer firms, particularly regarding the integration of AI within their R&D activities. To understand the strategic responses of these peer firms, we leverage the comprehensive U.S. bans on Huawei as a pivotal case. The year 2018 marked the beginning of the U.S.-China "technology cold war," with the U.S. targeting Chinese technological policies as a significant national security threat (Berman et al., 2023). Huawei, a key player in the 5G and ICT sectors, faced extensive bans from 2018 due to allegations of posing a security risk and threatening America's 5G leadership (Berman et al., 2023; Congressional Research Service, 2022). A key moment was the collapse of Huawei's deal with AT&T, driven by U.S. Congressional security concerns. This event was emblematic of escalating trade and technology tensions between the U.S. and China, which had global ramifications as countries like Australia and New Zealand excluded Huawei from their 5G networks due to security fears. The tensions escalated further with the arrest of Huawei's CFO, Meng Wanzhou, in Canada, related to alleged sanctions violations against Iran, adding a personal dimension to the broader corporate and geopolitical tensions.

We believe that the U.S. ban on Huawei provides an excellent opportunity to analyze how competing firms respond to unexpected external shocks for several reasons. Firstly, the sudden and unanticipated nature of the U.S. bans on Huawei creates a perfect scenario to study the impact of S&T conflicts on a firm's R&D strategies. Secondly, these bans have severely impacted Huawei's operations, threatening its existence and leading to a sharp decline in sales, which presents significant challenges for the company (Bueno, 2021; Economist, 2022). Additionally, the U.S. government's objective behind the bans was to slow down Huawei's rapid S&T progress (Berman et al., 2023), demonstrating the profound effects of such external shocks on the sector and underscoring the importance of monitoring how these firms adjust their R&D approaches.

Drawing from prior studies (Angrist and Pischke, 2009), we employ the differences-in-differences (DD) model to assess the impact of the 2018 US-imposed bans on Huawei for national security reasons, specifically on the integration of AI within the R&D activities of Huawei's peer firms. Our findings suggest that these bans have indeed prompted greater integration of AI into R&D processes. This is largely due to AI's versatility, which allows companies to circumvent potential targeted restrictions. Additionally, our analysis explores the role of institutional heterogeneity and cognitive perception. Our empirical results indicate that state-owned enterprises (SOEs) are more inclined to enhance their AI capabilities as they are more vulnerable to subsequent bans. Similarly, firms that has higher perception of threat to technology sovereignty tends to increase their investment in AI technologies.

3.2 Deglobalization, Institutional Clash, And Conflicts Over S&T

Globalization stands as a pivotal force, significantly influencing global economies and international business landscapes (Guillén, 2001; Rugman and Verbeke, 2004; Verbeke et al., 2018). Globalization refers to the process of intensifying worldwide interconnectivity, mobility, and imagination (Steger et al., 2023), which brings both opportunities and risk to the firm survival and operation in this period. (Steger et al., 2023). On one side, it provides firms with unparalleled opportunities to tap into broader markets, enhance resource accessibility, and reduce operational costs (e.g., Verbeke et al., 2018; Alcácer, Cantwell and Piscitello, 2016). However, alongside these benefits, globalization introduces considerable uncertainties and challenges to the survival and functionality of businesses. For instance, globalization amplifies competition (Witt, 2019), raises barriers through cultural (e.g., Tihanyi et al., 2005) and institutional differences (e.g. Salomon and Wu, 2012), and exposes firms to geopolitical conflicts (e.g., Han et al., 2024), underlining the complexity of navigating the globalized business environment. The presence of both opportunities and potential risks compels firms to design and implement strategies aimed at capturing advantages while mitigating potential risks.

In recent decades, we have witnessed escalating challenges to globalization. For instance, these challenges stem from geopolitical tensions (e.g., Cui et al., 2023), environmental concerns (e.g., Christmann and Taylor, 2001), rising nationalism (e.g., Luo, 2022; Balabanis, Diamantopoulos and Mueller, 2001), technological disruption (e.g., Han et al., 2024), supply chain vulnerabilities (e.g., Ciravegna and Michailova, 2022), and terrorism (e.g., Czinkota et al., 2020). As a result, we are witnessing a surge in conflicts and a noticeable shift towards deglobalization, underscored by the emergence of nationalism as a counterbalance to globalization. Illustrative of this trend are significant events such as the Brexit referendum, the escalation of the trade war between China and the United States (Jacob et al., 2022), and the United States' implementation of anti-dumping policies targeting Chinese exports (Huang et al., 2023). These instances highlight the growing tensions and challenges within the globalized world, signaling a reevaluation of international relationships and economic strategies. These emerging challenges have far-reaching impacts on a firm's survival and operations, compelling firms to re-evaluate and reshape their decision-making processes in response to the evolving challenges of globalization.

Specifically, Science and Technology (S&T) have emerged as the primary battleground for superpowers competing for dominance in the era of globalization, underscoring the deeply politicized nature of S&T (Beugelsdijk and Luo, 2024). This competition is not merely about economic gain but is intricately linked to national interests and security imperatives. The intertwining of S&T development with both corporate financial goals and broader geopolitical strategies signifies a shift in how nations and corporations navigate the global landscape. Previous literature defines technology sovereignty (Edler,

2020) as a nation's or a group of nations' capability to independently produce or source critical technologies essential for their welfare, competitive edge, and autonomous decision-making without relying excessively on external entities. This framework illustrates that the rivalry in S&T extends beyond mere market competition; it encompasses a strategic contest for technological autonomy, economic security, and national power.

Amidst growing challenges to globalization, such as protectionism and geopolitical tensions, the struggle for dominance in S&T has intensified. Notable examples include the United States' sanctions on foreign companies (Han et al., 2024), and international disputes over intellectual property rights (IPR), particularly within the pharmaceutical sector. Furthermore, global tech giants like Meta, Google, Amazon, and Apple find themselves at the center of increasing regulatory scrutiny and challenges. These developments are emblematic of the broader trend of S&T becoming a focal point of international political and economic conflict. This politicization of S&T and the ensuing conflicts underscore a critical juncture in international business, where technological advancement and geopolitical strategy are inseparably linked. As nations and companies grapple with these challenges, the landscape of global S&T competition continues to evolve, highlighting the need for strategic foresight, collaboration, and innovation to navigate the complex interplay of interests that defines this new era.

3.2 The Huawei Controversy: National Security Concerns Behind the Global Bans

The competition for supremacy in S&T domain has become a defining arena for global superpowers, with the victor poised to lead future S&T advancements, particularly in AI and ICT industry (Lee, 2018). China, as the largest developing country, has emerged as a formidable force within this tech cold war, positioning itself as one of the largest and most powerful competitors for US. Consequently, Chinese firms, particularly the 5G titan Huawei, have been perceived by the United States as significant threats to their leading role in the tech competition. As a result, the year 2018 marked the beginning of what has come to be known as the U.S.-China "technology cold war", with the U.S. administration specifically targeting Chinese technological policies as a grave national security threat (Koetse, 2018; Berman et al., 2023). Huawei, a titan in the 5G and ICT arena, found itself at the center of this storm, facing stringent bans from 2018 onwards, under allegations of constituting a risk to U.S. national security and challenging America's preeminence in the nascent 5G sphere (Berman et al., 2023; Congressional Research Service, 2022).

The unraveling of this conflict was notably signaled by the collapse of Huawei's anticipated deal with AT&T, a development stemming from U.S. Congressional security concerns. This incident was not an isolated occurrence but a defining moment, emblematic of a significant upsurge in the U.S.-China trade and technological tensions. The impact of these developments was felt worldwide, as nations like Australia and New Zealand decisively excluded Huawei from their 5G networks over security fears, reflecting a more synchronized and stringent international posture than Huawei had previously faced. The situation further escalated with the arrest of Huawei's CFO, Meng Wanzhou, in Canada, linked to allegations of sanctions violations against Iran, adding a personal dimension to the corporate and geopolitical tensions. Contrary to initial expectations that these bans might be short-lived, they have proven to be enduring, lasting for over five years and highlighting the persistent nature of these disputes. The comprehensive bans on Huawei emerged as a largely unanticipated and exogenous challenge. The bans on Huawei can be conceptualized as the case of "conflicts over S&T" highlighting the deepening rivalry between the United States and China within the high-tech industry (Economist, 2019). These actions significantly impact Huawei's sales of 5G-related equipment in the western markets, reflecting a targeted effort by the U.S. to curtail

Huawei's rapid development in S&T and, by extension, China's ambitions to dominate key high-tech industries (Berman, 2023; Congressional Research Service, 2022).

The sudden bans against Huawei represent a complex challenge not only for the company itself but also for its industry peers (Jacob et al., 2022). These bans are not merely reactions to isolated infractions, such as human rights violations or embargo breaches, but are primarily driven by perceived threats to national security (Berman, 2023; Congressional Research Service, 2022). This distinction is crucial because it suggests a broader implication: if one company within a sector is deemed a security risk, peering firms may also come under scrutiny. The rationale for such bans often includes the interlinked nature of the technology ecosystem and the sharing of components and data, which can potentially expose multiple firms to the same vulnerabilities. Furtherly, Huawei stands as the largest provider of 5G and AI technologies in China, cementing its position as a leader in the global tech industry. As of 2018, Huawei has deployed over 50% of the 5G infrastructure across China, significantly more than any other company. Additionally, its advancements in AI have positioned it at the forefront of innovation, with substantial investments amounting to billions of dollars annually to develop cutting-edge AI applications for industries ranging from telecommunications to healthcare. As a result, if a leading firm like Huawei is banned for national security reasons, there is a significant risk that peer companies could face similar bans. This scenario creates a precedent where national security concerns can trigger a chain reaction of restrictions within the industry.

Huawei's pivotal position in China's 5G and CIT industries. Initially, these bans create an unfavorable business environment by hindering Huawei's product sales in international markets, which in turn disrupts the supply chain dynamics for these firms. Consequently, faced with this immediate adversity, firms are compelled to strategically reposition themselves to react the unexpected bans. Moreover, the persistence of these bans introduces long-term uncertainties, stemming from the protracted nature of the technology sovereignty dispute between China and the US, particularly in the context of 5G technology. This enduring state of uncertainty necessitates firms to undertake measures that safeguard and enhance their long-term competitiveness in the global market.

Furthermore, beyond economic uncertainties, the bans also provoke complexity of legitimacy for the affected firm (e.g., Lee, 2018). Specifically, the bans prompt varying perceptions of legitimacy for the affected firm, as legitimacy is contingent upon the diverse viewpoints of different stakeholders. In our context, the origin of the controversy stems from the United States' decision to implement bans on Huawei, citing allegations that the company poses a threat to national security. This accusation directly impacts affected firm’s legitimacy in the international arena (Berman, 2023; Congressional Research Service, 2022). The narrative in the U.S. paints Huawei in a negative light, attributing to it and its peer companies a diminished standing in terms of legal and ethical acceptance (Hong, 2021). Conversely, from the perspective of domestic stakeholders in China, the perception of legitimacy undergoes a dramatic shift. The accusations against Huawei and its peer firms of contaminating legitimacy, framed as threats to national security, are met with disagreement by domestic stakeholders. Within this context, Huawei and its peers are perceived as victims of unjust treatment by the U.S., subjected to what many consider to be a form of bullying.

3.3 Bans on Huawei and Integration of AI Within R&D Activities

Given this context, it is particularly intriguing to analyze how geopolitical tensions influence strategic responses from peer firms, especially in terms of R&D strategies. Our focus is primarily on the degree to which AI is being integrated within these R&D efforts. This emphasis on AI is crucial, as it is at the heart of the escalating technological rivalry between China and the United States, driving much of the competition between these two global superpowers (Koetse, 2024; The Strait Times, 2024; Webster and Hass, 2024). Additionally, the increasing incorporation of AI in R&D signifies its pivotal role in fostering innovation within these activities (Jia et al., 2024). By examining these dynamics, our research aims to provide insights into how firms strategically respond to geopolitical conflicts by reshaping their technological capabilities, specifically through enhanced integration of AI in their research and development processes.

One possibility is that the peering firm might decrease the integration of AI within their R&D activities. This would be consistent with research suggesting that the uncertain environment may lead the firm to decrease their exploration and exploitation because exploration requires a longer learning curve (Stagni et al., 2019). Additionally, previous literature has disclosed the cost to integrate AI within R&D. This is echoed by a recent study finding that the integration of AI within R&D activities is negatively related to market value activities (Bowen et al., 2024). Combining the cost of integrating AI and uncertainty in the future should decrease their engagement in the AI domain. This is consistent with the research showing the cost of AI. Firms might decrease their exploration in the AI domain to mitigate the uncertainties brought by the technology.

However, there is an alternative argument for the opposite prediction that affected firms will increase the integration of AI within their R&D activities after the bans on Huawei in 2018. This strategy choice aligns with the real option theory, suggesting that exploration represents a future possibility, especially crucial for firms operating in uncertain environments (e.g., Belderbos, et al., 2019, 2020). Following this fashion, we expect that firms will be motivated to invest in AI-related innovation. Furtherly, AI, recognized as a general-purpose technology, acts as a catalyst for the recombination of new technologies and the identification of potential underlying patterns (Crafts, 2021). With AI, there is a heightened efficiency and competitiveness (Agrawal et al., 2019). This is echoed by the recent finding that firms increase their recombination after applying AI to their R&D activities (Agrawal et al., 2019). Therefore, to preserve their long-term competitive advantage, firms should make more exploration in the AI domain.

We favor the latter explanation, wherein affected firms increase the integration of AI within R&D activities, because the integration of AI not only enables long-term competitive advantage but also maintains flexibility. AI acts as a general-purpose technology, which can be reapplied to other innovation domains (Craft, 2021). These unprecedented and unforeseen bans have placed Huawei in a precarious position and cast a shadow of adversity and uncertainty over its industry peers. Anticipating potential collateral impacts, these firms might be compelled to adopt diversification strategies to mitigate risks and establish distinct operational paradigms, thereby circumventing the implications of potential bans. In addition, the adoption of AI significantly enhances the flexibility of these peer firms (Sanchez, 1995; Zhou and Wu, 2010). The inherent versatility of AI technologies enables broad applicability across various domains, thus ensuring sustained operational flexibility (Craft, 2010). This strategic adaptation facilitates the navigation of the complexities engendered by external geopolitical pressures, preserving the firms' innovative capabilities and adaptability in a dynamically evolving technological ecosystem. This is particularly significant in the context of the US government's bans on Huawei due to national security concerns. Peer firms are at risk of facing future prohibitions, which makes investments in a specific domain of knowledge particularly hazardous. Such bans could render existing investments in R&D activities as sunk costs. Integrating AI within these R&D activities could potentially mitigate this risk, helping firms to safeguard their investments even if they face bans in the future.

Furthermore, the bans on Huawei extend beyond economic impacts, leading to a complexity of the perception of legitimacy among various beholders. We expect that investing in AI represents not just a technological advancement but a strategic alignment with national priorities in China, which in turn can significantly enhance a firm's legitimacy among domestic beholders. This strategic sector, emphasized by the Chinese government as a cornerstone of the country's future economic and technological development, offers a unique opportunity for firms to position themselves at the forefront of innovation and national pride (State Council, PRC, 2017). By channeling resources into AI, companies can signal their commitment to contributing to China's global competitiveness and technological sovereignty. This investment does more than just align with national goals; it acts as a potent mechanism to enhance the perceived legitimacy of domestic stakeholders. In a context where national priorities are tightly interwoven with economic strategies, firms that invest in AI are viewed as key players in advancing China's ambitions (State Council, PRC, 2017). This perception goes a long way in strengthening a firm's standing and legitimacy within the country. Stakeholders, ranging from government bodies to consumers and local businesses, tend to view these firms as pivotal to the nation's success, thereby fostering a supportive and resource-rich environment for their growth. Moreover, the focus on AI investment can be seen as a strategic response to international challenges. This domestic legitimacy, built on the foundation of strategic sector investment, can act as a springboard for firms, allowing them to navigate international uncertainties more effectively.

In essence, by investing in AI, firms not only contribute to China's technological and economic ambitions but also solidify their own foundation for growth, resilience, and competitiveness on the global stage. Therefore, we hypothesize that.

Hypothesis 1: The Bans on Huawei will lead to the increased integration of AI within their R&D activities.

3.4 Boundary Condition

So far, we have posited that the unexpected bans on Huawei could systematically influence the integration of AI within their R&D activities, prompting affected firms to take steps to mitigate short-term challenges, secure long-term competitive advantage, and align with national interests. The existing literature also highlights critical boundary conditions meriting further investigation. Firstly, the institutional characteristics of a firm may act as a catalyst, reshaping its approach to S&T conflicts. It is, therefore, theoretically compelling to explore how institutional differences may influence firms' preferences for integrating AI within their R&D activities. Secondly, research has shown that cognitive factors can impact firms' R&D endeavors (DiMaggio and Powell, 2000). Considering the varied cognitions regarding technology sovereignty (Elder et al., 2020; 2023), examining heterogeneities across different perceptions could deepen our understanding of how the Huawei bans affect AI integration in R&D activities. Accordingly, we propose hypotheses concerning these two significant boundary conditions derived from the literature: institutional environment heterogeneity and cognitive perceptions of technology sovereignty.

3.4.1 Institutional environment heterogeneity

The literature on innovation highlights the pivotal role of the institutional environment in developing and navigating innovation. A firm's institutional environment necessitates its adherence to certain norms and practices to gain legitimacy and access essential resources, thereby sustaining competitive advantage (Hrisch, 1975; DiMaggio and Powell, 2000). Among various institutional characteristics, state ownership stands out, especially in the context of Chinese enterprises, where it significantly influences decision-making processes (Greve and Zhang, 2017; Huang et al., 2017). In China, the government and its affiliated institutions play a crucial role as sources of legitimacy, exerting both normative and regulative pressures on firms to adopt specific practices. State-owned enterprises (SOEs) are particularly subject to government influence, more so than their private counterparts. The literature thus underscores the importance of institutional characteristics in shaping firm decisions makings (Huang et al., 2017).

In this study, we argue that State-Owned Enterprises (SOEs), as opposed to private companies, are more likely to incorporate AI into their research and development (R&D) initiatives due to two primary factors. Firstly, SOEs are perceived as a distinctive institutional element of the Chinese economy (e.g., Huang et al., 2017). In comparison to non-SOEs, they are more susceptible to future bans as they are often seen as extensions of the Beijing government, thus potentially posing a national security threat (South China Morning Post, 2022), which increase the risk of being banned in the future.

Secondly, AI is considered a pivotal industry for China's economic future. By embedding AI technologies within their R&D processes, SOEs can not only enhance their operational efficiency and innovation flexibility but also align themselves with the national strategic objectives. This alignment is crucial, as it supports the government's ambitions to position China as a leader in the global technology sector.

Therefore, the integration of AI into R&D activities is not merely a technological upgrade but also a strategic maneuver to fortify national interests and maintain competitive advantages on the international stage. This strategic integration can help mitigate the impact of any potential bans by demonstrating the proactive adaptation of SOEs to global standards and expectations in critical technological domains.

Here, we predict that compared to non-state-owned enterprises, state-owned enterprises are more likely to integrate AI within R&D activities in response to Huawei's ban by Trump's administration.

Hypothesis 2: The positive role of the bans on Huawei and the integration of AI within R&D activities is stronger for those firms are state-owned enterprise.

3.4.2 Cognitive perceptions of threat to technology sovereignty

The cognitive perception of the nature of events has consistently been a critical factor in driving innovation and shaping business strategies (DiMaggio and Powell, 2020). This perception deeply influences how companies interpret events and, consequently, how they formulate their strategic responses. Specifically, in the context of the restrictions placed on Huawei, we expect that firms' understanding of these bans significantly impacts their actions and alignment with broader objectives such as national interest and technology sovereignty.

Companies that view the bans on Huawei as detrimental to the principle of technology sovereignty are more likely to take actions toward the unexpected bans. This perception fosters a stronger motivation within these firms to mitigate the adverse effects of such policies and to enhance their alignments with national interests, thereby actively participating in the battle for technology sovereignty (Elder et al., 2020; 2023). This alignment not only serves as a protective measure but also as a strategic move to ensure their resilience and adaptability in a rapidly changing global technological landscape. On the other hand, this lack of perceived threat results in a diminished sense of urgency to adapt or respond to the changing regulatory environment. Consequently, these firms may find themselves at a strategic disadvantage, as they fail to anticipate or react to shifts in policy that could impact their operations or competitive positioning.

Hypothesis 3: The positive role of the bans on Huawei and the integration of AI within R&D activities is stronger for those that perceived the bans as a threat to the technology sovereignty.

3.5 Research Design and Identification Strategy

In our study, we adopt a quasi-experimental study to investigate the influence of the appearance of geopolitical conflicts on R&D strategies. Specifically, we focus on the unexpected bans on Huawei, a series of restrictions on the Chinese high-tech titan in the year 2018, as the exogenous shock. The appearance of bans on Huawei restricts Huawei's accessibility to the US market and restricts Huawei's R&D activities (Berman et al., 2023; Congressional Research Service, 2022). In this design, our treatment group consists of peering firms to Huawei, which are most likely to be directly affected by this the unfavourable environment brought by the appearance of geopolitical conflicts. The control group comprises comparable firms to peering firms within the same industry (Angrist and Pischke, 2009). Our empirical analysis compares the extent of integration of AI within the R&D activities between two groups using a difference-in-differences (DD) research design.

The appearance of bans on Huawei by Trump's administration provides a unique and important setting to examine the role of technology sovereignty conflict on R&D activities for several reasons. First of all, the U.S. government's imposition of bans on Huawei was both abrupt and unforeseen, providing the setting for us to capture the causality of S&T conflicts on the firm's R&D strategies. This unpredictability, likely driven by national security concerns and the desire to balance both economic-wise and legitimacy-wise considerations, creates and ideal setting for capture causal relationship of geopolitical conflicts on firm's innovation strategies (Berman et al., 2023). The strategic underplay and lack of prior disclosure by the U.S. were possibly aimed at preventing Huawei and his peering firms from pre-emptively countering the bans' effects, maximizing the influence of bans. Additionally, maintaining secrecy was crucial for internal policy coordination and controlling the timing and narrative of the bans. As a consequence, this setting allows for a clearer understanding of how AI technologies are integrated into R&D activities as a reaction in terms of strategic reorientation and innovation during significant S&T conflicts.

Secondly, the U.S. imposition of bans on Huawei has significantly constrained its operations and even its survival (Huawei, 2021; Economist, 2022). This has led to a noticeable plummet in sales as Huawei grapples with the challenges posed by these restrictions. Consequently, the company has been compelled to redirect its focus towards the domestic market, compensating for the loss of access to external markets. As a titan in the ICT and 5G industry, the ramifications of the bans on Huawei extend far beyond the company itself, impacting peering firms. The far-reaching influence of these bans underscores the pivotal role

Huawei plays in the global tech landscape, highlighting how measures against such a key player can reverberate through the entire sector.

Additionally, given Huawei's status as one of the largest firms in the world, especially in the sectors of 5G and AI, we can utilize publicly available data to identify peer companies. Huawei's market dominance and broad coverage in these key technological areas allow us to access and analyze comprehensive data sets that reveal which companies operate within the same sphere and may be considered its peers. This information is crucial for understanding the competitive landscape and assessing which firms are most likely to face similar challenges or opportunities.

Moreover, considering the U.S. government's reasons for imposing bans on Huawei reveals that the primary aim was to curb Huawei's swift advancements in S&T. This indicates the significant influence of this external shock on S&T, highlighting the necessity to observe the affected firm's reaction, especially in terms of research and development (R&D) activities. Unlike anti-dumping policies, which usually target low-end manufacturing sectors, the bans against Huawei—a company known for its R&D intensity—carry wider ramifications (Huang et al., 2023). These bans are expected to negatively affect not only Huawei's R&D endeavours but also the activities of peering firms The U.S. government's strategic maneuver, characterized by the bans' sudden and unexpected implementation, was likely designed to significantly disrupt Huawei's technological advances and its position in the global market. This situation emphasizes the critical need to assess the impact of U.S.-imposed bans on R&D activities, particularly for companies within Huawei's network.

Based on the proceeding reasons, we believe that the unexpected bans on Huawei provides one critical and ideal setting for us to examine the role of S&T conflicts on innovation.

3.6 Databases and Sample

In our investigation, we utilized two primary databases to examine the hypotheses: (1) the National Intellectual Property Administration (CNIPA), which offers a comprehensive repository of invention patents, and (2) the China Stock Market & Accounting Research database (CSMAR), which provides financial data for the sampled firms.

We begin our sample construction by identifying the treatment group, which consists of firms are most likely to be affected by the U.S. bans on Huawei in 2018. To ensure we work with reliable financial and market data, our analysis is confined to those firms listed on the Chinese stock market (i.e., public firm) (Han et al., 2024). The identification of these peer firms is meticulously carried out by analyzing their annual reports, specifically looking for companies that have direct ties to Huawei. Additionally, we narrow our focus to firms that are actively engaged in research and development (R&D) to minimize the inclusion of companies where R&D is not a primary focus. To this end, we include only those firms that have filed for at least one patent both before and after the imposition of the unexpected bans on Huawei in 2018, effectively excluding those not actively involved in R&D activities. Consequently, we collect data on these firms over a total period of six years. This duration includes three years before, the focal week of, and 2 years after the unexpected arrival of US bans on Huawei. In line with prior research, we concentrated on patent filings on a yearly basis, as this process is typically organized by year. Next to meet the requirement of the DD model, it is critical to identify a suitable control group (Angrist and Pischke, 2009). We select comparable firms in the same industry as the peering firm as the potential sampling firm.

Finally, in an effort to enhance the robustness of our causal inference, we implemented coarsened exact matching (CEM). This technique leveraged variables such as SOE, FIRM SIZE, ABSORPITVE CAPABILITIES, ROA, OPERATION CYCLE, QFII. These factors were chosen to match firms comparable in financial performance, governance structure, and

R&D capabilities. This matching was critical for balancing the characteristics of the two groups prior to conducting regression analysis, ensuring that our comparative study accurately reflects the nuanced impacts of the variables in question.

Overall, we believe that this quasi-experimental design is well-suited for our research question, and the DD research design with a matched sample further helps mitigate potential endogeneity concerns, strengthening the identification of the causal relationship between the role of technology sovereignty conflicts and integration of AI within R&D activities.

3.6.1 Variables

Dependent variables. *Integration of AI within R&D activities (i.e., AI-lization).* Recent developments have emerged in categorizing innovations related to AI technologies (Miric et al., 2023) discuss the importance of accurately categorizing innovations related to AI technologies, highlighting the challenges associated with such categorization. In this study, we adopt a new methodology proposed by Babina et al. (2020) to proxy human-talent investment in the AI domain (Babina et al., 2020; Boudreau et al., 2021). These scholars identified three core terms, Machine Learning (ML), Natural Language Processing (NLP), and Computer Vision (CV), that have minimal ambiguity in the classification with AI technologies. They then constructed a matrix for each job skills description to capture the relatedness of that skill to the three core AI terms, with higher relatedness indicating greater relevance of human capital to AI technologies.

Compared to AI-based (e.g., supervised machine learning) methods (Jia et al., 2023) and dictionary-based (e.g., keyword-based) method for classification, the core-terms-based method has two distinct advantages. First, AI-based methods and keyword-based identification strategies rely heavily on the accuracy and credibility of the core set or keyword list selected by researchers. Second, AI-based methods require a powerful computing platform and AI-specific knowledge. In this study, we utilize the core-terms-based methodology to identify AI-related patenting activities at the firm level through analysing patent filings (*AI-lization*). We adopt the same three core terms (i.e., the Chinese terms for Machine Learning, Natural Language Processing, and Computer Vision) as used by Babina et al. (2020).

We then calculate the relatedness of each unique word/term included in patent abstracts with these core terms, in order to identify AI-related patents filed by the firms. Specifically, for each unique word *j*, we calculate the coefficient W_j,

$$W_j = \frac{\#\ of\ patents\ with\ word\ j\ and\ any\ core\ word\ in\ patent\ abstract}{\#\ of\ patents\ with\ word_j} \quad (1)$$

The score of W_j ranges between 0 and 1. The value of 1 indicates that the unique word j is always associated with the core AI terms, indicating its importance to the AI-related innovation activities. The value of 0 indicates that the word j never appears in AI-related patents, indicating that this word has no relation with AI technologies. (The word list is attached in the appendix A). We then aggregate the relatedness at word level to patent level by averaging the W_j score of all unique word present in a patent's abstract, which is labeled as P_i. Based on the calculation of P_i, we create the variable *Ai-lization* by averaging the score of relatedness to AI-technique at t the patent level (P_i) across all patent fields filed by the firm in the particular year. The higher value of AAI indicates the related higher level of investment in AI domains.

Independent variable. Building on prior research, our study investigates the impact of spillover effect of US-imposed bans on Huawei by adopting a DD research design with a matched sample (Angrist and Pischke, 2009). To align with the requirements of this methodology, we have the following two primary independent variables: (1) the treatment dummy variable, which indicates whether the sampled developer belongs to the treatment or control group, and (2) the time dummy variable, which denotes whether the observation period falls before or after the bans imposed by US government.

Treatment. For Treatment, the variable will receive the value of 1 as the sampling firms belong to the treatment group. Otherwise, the variable will receive 0 as the sampling firms are included in the control group.

Time. For Time, a value of 1 is assigned to observation periods after the US imposed bans on Huawei, while a value of 0 is allocated to periods preceding US's bans.

Variables to construct the sub-sample. *SOE*. To examine the boundary conditions related to the heterogeneity of the institutional environment, we chose State-Owned Enterprise (SOE) status as the variable for constructing the subsample. Firms identified as state-owned enterprises are assigned a value of 1, while non-state-owned firms receive a value of 0. This binary classification allows us to divide our subsample based on the SOE status. By analysing the data through this variable, we can explore how the institutional backdrop, specifically the distinction between state-owned and private firms, influences the outcomes of our study.

Perception of threat to technology sovereignty. Building on existing literature, we measure the perception of threat to technology sovereignty sentiment within firms by employing a weighted count of words associated with anti-foreignness (Yue et al., 2023). This is achieved by dividing the count of words from a predefined list related to anti-foreign sentiment by the total number of words in the annual report. This method allows for a quantitative assessment of the perception of threat to technology sovereignty, providing insights into how companies perceive and potentially respond to foreign competition and policies. This metric offers a nuanced understanding of how perception of threat to technology sovereignty permeates corporate communications, reflecting broader attitudes and strategies toward international business dynamics. We separate the sub-sample by the median value of perception of threat to technology sovereignty to construct the subsample.

Control variables. To more effectively mitigate the impact of confounding variables, we have incorporated control variables from three distinct areas: (1) financial-related data, (2) governance structure-related data, and (3) innovation-related data. The rationale for controlling variables across financial data, governance structure, and R&D capabilities is grounded in the need to account for factors that significantly impact a firm's innovation process and its ability to manage and integrate AI technologies effectively. The control over financial-related data, including leverage, intangible assets, Price/Earnings (P/E) ratio, and firm size, is critical for several reasons. Leverage, or the ratio of a company's debt to its equity, can influence a firm's risk profile and its capacity to invest in new technologies, including AI. High levels of debt may limit a firm's ability to allocate resources to R&D activities due to the pressure to meet debt obligations, thereby affecting its innovation capabilities (O'rbien, 2003). Firm size is another crucial variable to control for, as larger firms often have more resources and a greater capacity for R&D investment. This variable helps to distinguish the effects of AI integration on R&D activities from those related to the scale of operations and resources available to the firm (Chaney and Devinney, 1992). Building on previous research, we further mitigate confounding effects related to financial factors by controlling for the Price-to-Earnings (P/E) ratio and intangible asset.

Besides, we also control the governance structure, including the dummy variables for state ownership and foreign investor presence, is vital to understanding the context within which AI integration occurs. State-owned enterprises (SOEs) may have different priorities, risk appetites, and levels of autonomy in their R&D decisions compared to private firms (e.g., Huang et al., 2017). These differences can significantly impact how AI technologies are integrated and utilized within R&D activities. By controlling for state ownership, the research can uncover the nuanced effects of AI integration across different types of ownership structures. Similarly, the presence of foreign investors can influence a firm's strategic direction and alignment of interest with different stakeholders (Shi et al., 2021). Foreign investors may bring different perspectives, expertise, and expectations regarding the adoption and integration of AI technologies. Controlling for this variable allows the research to consider the impact of diverse governance structures on the effectiveness and risks associated with AI in R&D. Finally, controlling for the count of patent applications as a proxy for R&D capabilities enables the assessment of a firm's baseline innovation output and technological prowess (Hall, 1999). Patent counts offer a measure of a firm's focus on innovation and its ability to generate new knowledge

3.6.2 Estimation strategy

To more precisely capture the causality and deal with the endogeneity concerns, following previous research, we employ the difference-in-difference (DD) model to estimate the impact of US imposed bans on Huawei and peering firm's integration of AI within their R&D activities. To meet the requirement for DD model, we need to construct the control firms that is comparable to the firms in the treatment. Specifically, we took the PSM method to match each competing firms (i.e., treatment) with a control firm (e.g., Arts and Fleming, 2018) within the same industry. In our study, we took one-to-one matching strategy according to the following criteria. First, we required that treatment and control firms share the same industry code. Second, we match the quantity of patent application because firms with distinct R&D capability usually exhibit different risk appetite and leverage different positioning strategy. Third, we match the debt ratio and return on assets (ROA) to ensure the financial comparability. Last, at the board-member level, we control match size of board member and average salary for the board member because governance-related factors also matter the decision makings on positioning. Given the dependent variable is the value bounded by 0 and 1, we employ the OLS model with fixed effect to examine question of how competing firms adjust their positioning to make response to the external threat at the focal firm. Specifically, we follow the following specification to estimate:

$$Y_{it}=a_t+\delta_i+\beta\times treatment_i\times post\_\text{ban } period_t+\gamma\times X_{it}+\varepsilon_{it}$$

where i indexes firm and t indexes year. Y_{it} is the primary dependent variable of our interest. Following the prior research using DD model, we mainly focus the interaction term β, which allows us to identify the change of dependent variable for the firms in the control group compared to those firm in the treatment group after the bans on Huawei imposed by US government. To rule out the confounding, we include X_{it} as the vector of control variables, and εit is the error term.

3.7 Results

To validate our research approach, we initially examine the comparability assumption (Angrist and Pischke, 2009). This process involves assessing the balance of covariates between the treatment and control groups prior to the U.S. bans on Huawei. The absence of significant differences in the average values of control variables for all proposed hypotheses indicates that the groups are suitably matched. Subsequently, we assess the assumption of parallel trends. There is no evident shift in trends before the bans imposed by Huawei, which supports the essential premise for the Difference-in-Differences (DD) model, thereby reinforcing the applicability in our setting.

Table 3 shows the results of testing hypothesis 1. Upon analyzing the coefficients of the DD term in model 1. We observe that the DD term is positive and significant at 5% level (β1=0.018,p=0.023). This suggest that peering firm of bans on Huawei will be more likely to integrate AI within R&D activities. The integration of AI within R&D activities can significantly aid firms in mitigating the challenges posed by uncertain environments. By leveraging AI, companies can enhance their resilience and adaptability, turning potential adversities into opportunities for growth and innovation. Furthermore, this strategic adoption of AI not only positions firms to gain a competitive advantage in the long term but also aligns their operations with national interests. Such alignment is crucial for firms looking to navigate regulatory landscapes and contribute to broader economic and technological goals, ultimately securing a pivotal role in shaping the future of their respective industries.

Table 4 presents the findings regarding the boundary conditions that influence the impact of technology sovereignty conflicts on the integration of AI within R&D activities. Specifically, Models 1 and 2 explore the boundary condition related to the heterogeneity of the institutional environment. Model 1 focuses on a subsample of state-owned enterprises, while Model 2 examines private firms. The results show that the coefficient of the difference-in-differences (DD) term in Model 1 is significant at the 5% level, indicating a notable impact of the bans on Huawei for state-owned enterprises. However, in Model 2, the coefficient of the DD term is not statistically significant, suggesting that the effect is not evident for private firms. These findings support our hypothesis that state-owned enterprises have a stronger imperative for alignment with national interests, highlighting how institutional context shapes the response to technology sovereignty conflicts.

Models 3 and 4 delve into the boundary condition of cognitive perception of technology sovereignty. Model 3 assesses firms with a stronger cognitive perception of threat to technology sovereignty, while Model 4 evaluates those with a relatively weaker cognitive perception. The findings reveal that the difference-in-differences (DD) term in Model 3 is positive and statistically significant, indicating that firms with a heightened awareness of perception of threat to technology sovereignty are more inclined to integrate AI into their R&D activities. Conversely, the DD term in Model 4 is not significant, suggesting that cognitive perception plays a crucial role in how firms respond to geopolitical conflicts over S&T. This implies that firms perceiving a higher level of perception of threat to technology sovereignty are more likely to proactively enhance their R&D capabilities through AI integration, highlighting the impact of cognitive perception on strategic decision-making in the face of international tensions.

3.8 Discussion

3.8.1 Research contribution

In this research, our paper explores the impact of bans on Huawei and their effects on the integration of AI within the R&D activities of peer firms. We engage with the existing literature in several significant ways.

Our study notably furthers the discourse on how firms strategically react to geopolitical conflicts, particularly in the science and technology sectors. The influence of such conflicts on corporate R&D strategies, particularly regarding patent quality and quantity, has been well-documented. For instance, Huang et al. (2024) have shown that anti-dumping measures positively affect both the number and quality of patent applications as firms prepare for future challenges. Similarly, Han, Jiang, and Mei (2024) introduced a patent-level variable for decoupling, showing that U.S. sanctions against Chinese high-tech firms result in increased decoupling on the Chinese side. However, these studies do not address firms directly affected by tariffs, missing a crucial layer of analysis on strategic responses at the firm level. Our research fills this gap by finding empirical evidence that firm will increase the integrations of AI within their R&D activities in response to geopolitical tensions over S&T.

Additionally, our work extends to the emerging field of AI in management literature. Although previous research has extensively explored the nature of AI technologies within R&D activities (Craft, 2021), there is a lack of focus on how AI can help firms manage risks associated with geopolitical conflicts. Our study contributes to this stream of discussion by suggesting that the integration of AI within R&D activities not only help the firm to mitigate the adversity brought by geopolitical conflicts but also help the firm to “escape” the potential adversity in the future.

Moreover, our paper expands the conversation about the impact of US-China geopolitical conflicts on the high-tech industry under the Trump administration (Han, Jiang, and Mei, 2024). While previous studies primarily focused on the influence of these conflicts on scientific research and innovation, we concentrate on the role of AI as a strategic tool in R&D processes. Specifically, we develop a methodological approach to construct variables that measure the extent of AI integration in innovation activities. Our findings highlight that US-China tensions not only affect the pace of innovation but also direct its course, underlining the strategic importance of AI in shaping industry responses to international disputes.

3.8.2 Limitation and future Research

The study provides insights into the application and impact of AI technologies in research and development (R&D) activities. However, the findings' generalizability is a notable limitation. This research was conducted within a specific context that may not fully represent the diverse industries and sectors where AI technologies are being integrated. The uniqueness of AI as a distinct method in R&D could mean that the results are more applicable to certain types of industries or technological domains than others. Consequently, while the study sheds light on the transformative potential of AI in R&D, the extent to which these findings can be extrapolated to other settings, industries, or forms of technology integration remains constrained. This limitation underscores the need for future research to examine the role of AI in R&D across various contexts, thereby enhancing our understanding of its broader applicability and impact.

The study predominantly utilizes patent data to analyze innovation, which presents another limitation. While patents are a valuable indicator of technological advancements and innovation efforts, they do not encompass all dimensions of innovation, particularly at the product level. This focus on patent data may not fully capture the multifaceted nature of innovation or the breadth of AI's influence on product development and enhancement. The reliance on patent data may overlook significant innovations that are not patented or those that manifest in non-patentable forms, such as process improvements or service innovations. Therefore, the study's insights into the impact of AI on innovation might be partial, highlighting the necessity for future research to incorporate more diverse measures of innovation. This could include case studies, product analysis, and other forms of intellectual property, to provide a more holistic understanding of how AI technologies influence innovation beyond patentable outputs.

Lastly, the study's primary reliance on quantitative data to assess the effects of conflicts on firms' methods of innovation marks a limitation. While quantitative approaches offer valuable insights through statistical analysis, they may not capture the full depth of how AI influences innovation practices within firms. The qualitative aspects, such as organizational culture, employee creativity, and the strategic decision-making process behind adopting AI in innovation, might be overlooked. These nuanced, qualitative factors play a critical role in shaping firms' innovation methodologies and outcomes. Consequently, the study's methodological focus might not fully reflect the complex, multifaceted nature of innovation in the context of AI. Future research could benefit from incorporating qualitative methodologies, such as interviews, case studies, and ethnographic research, to explore the subtleties of how AI technologies transform innovation practices within firms. This mixed-methods approach would provide a more comprehensive understanding of AI's impact on innovation, capturing both its measurable effects and the qualitative nuances that underlie innovation processes.

In sum, while the study contributes important insights into the integration of AI technologies in R&D and innovation, these limitations highlight areas for future research to build upon. Addressing these gaps will not only refine our understanding of AI's role in innovation but also guide firms, policymakers, and researchers in harnessing AI technologies for enhanced innovation outcomes.

3.9 Conclusions

In our study, we leverage the 2018 bans on Huawei as an exogenous shock and employ a differences-in-differences model to assess the impact of geopolitical conflicts over science and technology (S&T) on the integration of AI within R&D activities. Our research provides empirical evidence that geopolitical tensions, particularly those driven by national security concerns, positively influence the adoption of AI in R&D processes. This beneficial effect largely stems from AI's ability to help firms mitigate short-term disadvantages while securing long-term competitive edges. Importantly, the integration of AI also provides firms with enhanced flexibility to adapt to and possibly circumvent future prohibitions.

Furthermore, our findings indicate that the impact of these geopolitical shocks is markedly influenced by the institutional environment and the cognitive perception of the threat. Our analysis underscores that S&T conflicts serve as a catalyst for integrating AI within R&D operations, particularly in state-owned enterprises that may face future bans and substantial institutional pressures to align with national strategies. Additionally, cognitive perceptions play a critical role; firms that view bans as a threat to their technological sovereignty are more likely to intensify their integration of AI in their R&D efforts. This strategic alignment emphasizes not just a reactive stance but a proactive adaptation to shifting global tech dynamics.

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3.11 Tables

Table 1. Descriptive Analysis

	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Growth rate (1)	0.19	0.36	-0.86	3.62	1										
AI index (2)	0.2	0.16	0	1.14	0.015	1									
Absorptive capabilities (ln) (3)	3.22	1.38	0.69	8.65	0.036	0.212	1								
Leverage (4)	0.39	0.18	0.03	0.94	0.094	-0.063	0.297	1							
Market value (5)	2.2	1.24	0.8	11.99	-0.025	0.071	-0.136	-0.34	1						
State owned business (6)	0.22	0.41	0	1	-0.087	0.057	0.25	0.202	-0.073	1					
Foreign investor (7)	0.15	0.36	0	1	-0.021	0.044	0.164	0.017	0.062	0.094	1				
Operating cycle (ln) (8)	5.43	0.58	1.9	8	-0.03	0.106	-0.236	-0.123	0.094	-0.094	-0.056	1			
Size (ln) (9)	21.49	1.37	17.27	25.78	0.108	0.044	0.55	0.588	-0.309	0.37	0.14	-0.487	1		
P/E ratio (ln) (10)	4	0.91	2.02	10.87	-0.098	0.002	-0.212	-0.074	0.355	-0.042	0.002	0.263	-0.361	1	
Intangible asset (ln) (11)	0.04	0.03	0	0.31	0.022	-0.044	-0.018	0.106	-0.003	-0.032	-0.02	-0.008	0.036	0.106	1

Table 2. Results

	(1) Model1
Treatment X Time	0.018**
	(0.023)
Absorptive capabilities (ln)	0.013***
	(0.006)
Leverage	-0.011
	(0.770)
Market value	0.012
	(0.766)
State owned business	-0.014
	(0.462)
Foreign investor	-0.004
	(0.530)
Operating cycle	-0.001
	(0.959)
Size (ln)	-0.012
	(0.335)
P/E ratio (ln)	-0.127
	(0.399)
Intangible asset (ln)	0.242
	(0.375)
Constant	2,228
	0.748
Firm fixed effects	Yes
Industry fixed effects	Yes
Year fixed effects	Yes
Observations	0.018**
R-squared	(0.023)

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed
Note b: Model 1 employs OLS regression with individual and week fixed effects

Table 3. Subsample Analysis

	(1)	(2)	(3)	(4)
	Model1	Model2	Model3	Model4
Treatment X Time	0.038**	0.013	0.019*	0.018
	(0.024)	(0.180)	(0.091)	(0.169)
Absorptive capabilities (ln)	0.007	0.014**	0.027***	-0.001
	(0.258)	(0.012)	(0.000)	(0.924)
Leverage	-0.043	-0.001	-0.038	0.045
	(0.505)	(0.984)	(0.356)	(0.454)
Market value	-0.153**	0.022	0.027	0.018
	(0.035)	(0.622)	(0.697)	(0.721)
State owned business			-0.037	0.002
			(0.129)	(0.920)
Foreign investor	0.004	-0.006	0.002	-0.001
	(0.676)	(0.485)	(0.852)	(0.907)
Operating cycle	0.008	-0.000	-0.011	-0.005
	(0.652)	(0.998)	(0.466)	(0.712)
Size (ln)	-0.017*	-0.009	-0.020	-0.004
	(0.076)	(0.611)	(0.130)	(0.796)
P/E ratio (ln)	-0.160	-0.120	-0.069	-0.251
	(0.521)	(0.481)	(0.641)	(0.276)
Intangible asset (ln)	0.117	0.201	0.449	0.335
	(0.779)	(0.540)	(0.159)	(0.258)
Constant	465	1,755	1,046	1,046
	0.870	0.723	0.787	0.793
Firm fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	0.038**	0.013	0.019*	0.018
R-squared	(0.024)	(0.180)	(0.091)	(0.169)

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed
Note b: Model 1 employs OLS regression with individual and week fixed eff

4. IN SEARCH OF SOLUTIONS: IMPACT OF MACHINE INTELLIGENCE ON KNOWLEDGE CROWDSOURCING

4.1 Introduction

As a form of problem solving, knowledge search is a central task for innovations, underpinned by a search process whereby innovators identify solutions to problems and create new solutions through knowledge recombination (Fleming, 2001; Lerner & Stern, 2012; Nelson & Winter, 1982; Posen et al., 2018). Prior research dissects the knowledge search process into two distinct yet interconnected components: problem formulation, where a problem is purposefully defined, and solution finding, where a suitable solution is assessed and adopted to address the identified problem (Einstein & Infeld, 1938; Katila & Ahuja, 2002; Lopez-vega, Tell & Vanhaverbeke, 2016; Newell & Simon, 1972). Numerous studies have focused on the intricacies of the search process, aiming to improve its outcome and facilitate the generation of new knowledge and innovation (Baer, Dirks, & Nickerson, 2013; Dutt & Mitchell, 2020; Gavetti & Levinthal, 2000; Knudsen & Levinthal, 2007; Kneeland, Schilling, & Aharonson, 2020; Lopez-Vega et al., 2016; Nickerson, Yen, & Mahoney, 2012; Zhang & Yang, 2022).

Despite these efforts, empirical studies have rarely explored each component of knowledge search independently due to the inherent interconnection between problem formulation and solution finding and the challenges in empirically teasing them apart (c.f., Dutt & Mitchell, 2020; Lopez-Vega et al., 2016; Zhang & Yang, 2022). Dominant proxies for knowledge search, such as patents or products, usually “include a description of a technical problem and a solution to that problem” (Katila & Ahuja, 2002, p. 1186). While there are initial empirical attempts to delve into problem formulation (Baer, Dirks, & Nickerson, 2012; Kaplan, 2008; Zhang & Yang, 2022), less attention has been given to solution finding, causing limited understanding of the efficiency and effectiveness in obtaining and evaluating solutions after a problem is formulated (Berchicci, Dutt, & Mitchell, 2019; Felin & Zenger, 2014; Gavetti & Levinthal, 2000; Posen et al., 2018). However, solution finding is particularly relevant since it is common to have a pool of solutions corresponding to a formulated problem, leading to the question of how distinctive outcomes of knowledge search are reached and dictating the heterogeneous technological trajectories/standards developed by inventors (Einstein & Infeld, 1938; Katila & Ahuja, 2002). Meanwhile, scholars long maintain that the search for problem solutions commonly falls prey to humans' cognitive limitations, leading to a growing stream of research on the role of technology, especially digital technologies (e.g., Austin, Devin, & Sullivan, 2012; Dougherty & Dunne, 2012; Furman & Teodoridis, 2020; Raish & Fomina, 2024), in shaping and renewing knowledge search processes. However, a prominent question remains as to how the advent of artificial intelligence (AI), noticeably performing cognitive functions better than humans do, may reshape the previously human-centric process of knowledge search and its specific components (Murray, Rhymer, & Simon, 2021).

To address these two gaps, we empirically explore how AI-supported intelligent machines affect knowledge search outcomes by influencing individuals' solution finding process. AI is seen as a potential resource that either substitutes for human efforts or augments human decision-making by reducing biases (Afuah & Tucci, 2023; Raisch & Krakwoski, 2021), with particular efficacy in problem-solving where advanced learning algorithms are used to automatically link known solutions to well-defined problems (Bianchini et al., 2022; Brynjolfsson & McAfee, 2017; Russell & Norvig, 1995; Waardenburg, Huysman, & Sergeeva, 2021). The recent emergence of artificial intelligence-generated content (AIGC) technologies, which create new data and highly-tailored answers during Q&A conversations in natural human language (e.g., Burtch, Lee, & Chen, 2023;

Sanatizadeh et al., 2023), further assists knowledge search in more exploratory tasks where new solutions need to be created for unexplored problems (Raisch & Fomina, 2024). Research shows that AI can help individuals cope with knowledge explosion within domains, facilitate cross-domain recombination, reduce uncertainty in recombination, and generate distant solutions (Agrawal, McHale, & Oettl, 2023; Afuah & Tucci, 2023; Amabile, 2020). That said, two salient issues cast clouds over the promises of AI. First, scholars repeatedly caution about the myopia of machine intelligence that could limit solutions and their novelty (Balasubramanian, Ye, & Xu, 2022; Bianchini et al., 2022; Lindebaum, Vesa, & den Hond, 2020). Second, while exploratory tasks like problem-solving require a hybrid approach combining human and machine intelligence in search (Von Krogh, 2018), humans and especially domain experts consistently display AI aversion in joint tasks (Allen & Choudhury, 2022; Liu et al., 2023; Wang, Gao, & Agarwal, 2023), due to distrust in AI's competences or prejudice against AI agency (Turel & Kalhan, 2023; Vanneste & Puranam, 2024). Those two issues are often intertwined, leading to difficulties in assessing whether AI's impact on search outcomes is due to its effectiveness or humans' aversion.

Our analysis utilizes a unique context of hybrid knowledge search to address our research questions amid the aforementioned issues. We exploit the unexpected arrival of the groundbreaking AIGC technology, ChatGPT, and examine individuals' Q&A activities on StackOverflow, a leading online forum for technical discussions of coding knowledge. The context offers three important advantages. First, Q&A forums, by nature, break down the search process into problem formulation and solution finding. StackOverflow allows us to track individuals' questions and answers separately, so that we can partial out the effect of problem formulation and alleviate the endogeneity concerns over prior research. Second, StackOverflow serves as a platform for sourcing new knowledge regarding non-routine and sometimes idiosyncratic technical challenges (Zhang & Yang, 2022), making it an apt setting for studying AI's role in aiding complex problem-solving. Third, ChatGPT offers a new source of machine-generated knowledge that can be combined with human expertise in providing tailored solution alternatives for individuals to evaluate, rendering possible a hybrid approach to problem solving that particularly suits exploratory tasks. While anecdotal evidence suggests that ChatGPT's contents have widely populated StackOverflow, the answers continually appear as generated and provided by human experts, and the use of AIGC remains hard to detect (StackOverflow, 2022a). As a result, individuals are likely oblivious to the hybrid interaction behind the generation of a solution alternative. Given that disclosing the degree of involvement by human vs AI may distort the perception about the output (Gnewuch et al., 2023), it is critical to use a context that can contain individuals' AI aversion while teasing out AIGC's impact on solution finding.

Utilizing detailed data from StackOverflow, we compare, through a difference-in-differences design, search outcomes between individuals exposed to ChatGPT and similar individuals who did not have access to this technology. Our research demonstrates that the emergence of ChatGPT significantly increases the volume of answers (potential solutions) to questions raised by individuals, when holding constant the way these problems are formulated. This finding suggests that 1) AIGC can enable hybrid problem-solving as expected and make more individuals appear as domain experts, and 2) this hybrid approach may improve the efficiency of solution search. However, the increase in potential solutions does not translate into a higher likelihood of obtaining satisfactory solutions. The unchanged rate of answer acceptance by individuals indicates that more solution alternatives do not necessarily result in more effective search. Additionally, we observe an increase in the time required to locate a satisfactory solution and an increase in follow-up discussions. These findings collectively suggest that while individuals are afforded access to an expanded spectrum of potential solutions generated by a combination of human and machine intelligence, they concurrently encounter escalating costs in evaluating and selecting relevant solutions from this enlarged array of choices. Furthermore, our analysis reveals that the impact of ChatGPT varies significantly depending on the individuals' search experiences. This heterogeneous effect underscores that the utility of AIGC in facilitating knowledge search is contingent upon the individuals' capabilities in evaluating solutions, suggesting that solution evaluation remains subject to cognitive limitations (Knudsen & Levinthal, 2007; Piezunka & Dahlander, 2015) and may be an overlooked bottleneck impeding machine-aided knowledge search.

4.2 Theoretical Background

4.2.1 Knowledge search: solution finding

To situate our paper in the search literature, we first provide a brief overview of the theoretical background of the knowledge search process. Rooted in the Schumpeterian school and Carnegie's school of thinking, knowledge search is essentially a form of problem-solving that entails the search, creation, acquisition, integration, and recombination of knowledge (Winter, 1984; Katila & Ahuja, 2002; March, 1991). This type of search, specific to innovation context, is a specialized form of problemistic search that focuses on technological challenges rather than broader organizational issues (Cyert & March, 1963; March, 1991; Posen et al., 2018). Accordingly, as with any problem-solving activities, the process of knowledge search comprises two distinct components, problem formulation, and solution finding (Katila & Ahuja, 2002; Newell & Simon, 1972; Posen et al., 2018). Problem formulation is a strategic process of identifying and articulating the challenges or anomalies in innovation tasks (Baer et al., 2012; Zhang & Yang, 2022). Correspondingly, solution finding involves locating, evaluating, and selecting appropriate solutions to the identified problem (Felin & Zenger, 2014; Gavetti & Levinthal, 2000; March, 1991). These two components are interconnected, with problem formulation guiding and influencing the outcome of solution finding (Csaszar & Levinthal, 2016; Gavetti & Levinthal, 2000; Fleming & Sorensen, 2004; Leiponen & Helfat, 2010).

The processes of knowledge search are crucial, since the effectiveness and efficiency of finding new and innovation-supporting knowledge are significantly influenced by the combined processes of problem formulation and solution finding (Baer et al., 2013; Gavetti & Levinthal, 2000; Kaplan, 2008; Von Hippel & Von Krogh, 2015). Research in this literature has progressed towards a conceptual understanding of these processes and has empirically examined factors that facilitate or hinder them (Baer et al., 2012; Dutt & Mitchell, 2020; Gavetti & Levinthal, 2000; Knudsen & Levinthal, 2007; Kneeland et al., 2020; Lopez-Vega et al., 2016; Nickerson et al., 2012; Zhang & Yang, 2022). Studies on problem formulation have identified that limited information processing capabilities, cognitive biases, personal interests, proximity to problem sources, and technological advancements all essential in shaping this specific process (Baer et al., 2012; Dutt & Mitchell, 2020; Zhang & Yang, 2022). While there has been progress in understanding problem formulation, research on solution finding is underdeveloped, primarily due to the difficulty in separating this process from problem formulation (Katila & Ahuja, 2002). Patents and products, which are often used in empirical studies, embody both processes, as they represent a question and its answer simultaneously (Kaplan & Vakili, 2015; Walker, 1995). Consequently, while there is evidence of problem formulation influencing solution finding (Knudsen & Levinthal, 2007; Kneeland et al., 2020; Nickerson et al., 2012), the extent to which solution finding is affected by external factors remains less understood.

Among these factors, of particular interest is the impact of technological shock on knowledge search processes, as a growing stream of research has demonstrated that advancements in technology can motivate search and alter the knowledge search process (e.g., Zhang & Yang, 2022). Recently, the recent advancements in AIGC technologies that drastically changed how individuals search for new knowledge represents one such technological shock, given its disruption on the previously human-centric solution finding process and its potential ability to extend human cognition boundaries (e.g., Burtch et al., 2023; Murray et al., 2021; Riveros, Zhang, & Luo, 2023; Sanatizadeh et al., 2023).

4.2.2 AIGC technologies and solution finding

AI technologies are increasingly recognized for their role in transforming innovation processes (Haefner et al., 2021; Mariani et al., 2023; Raish & Fomina, 2024), naturally impacting knowledge search activities. Beyond the parallel of the problem-solving processes between machine learning (a key component of AI) and knowledge search, researchers have identified several ways in which AI influences knowledge search and, consequently, solution finding. First, AI enhances the information processing capabilities of individuals, alleviating the burden of managing extensive knowledge, increasing efficiency in processing existing knowledge, and reducing cognitive limitations associated with knowledge accumulation (Haefner et al., 2021). Such enhancement allows for the efficient and comprehensive summarization of existing knowledge within established domains, expediting the solution finding process (Bianchini et al., 2022). Furthermore, AI facilitates the connection of distant information, potentially breaking down barriers across different knowledge domains. Such a connection can uncover previously unrecognized opportunities for knowledge recombination and reveal innovative and unexpected solutions (Amabile, 2020; Raish & Krakowski, 2021; Bianchini et al., 2022; Haefner et al., 2021). Lastly, AI has the potential to accelerate the identification of viable solutions. This acceleration is achieved through machine learning-enhanced experiments, where the effectiveness of proposed solutions can be preliminarily tested and evaluated (Gupta et al., 2018). These advancements suggest that AI is reshaping how knowledge is searched and how solutions are identified and validated.

Despite the significant impacts of AI technologies on solution finding, a comprehensive understanding of their generalized influence remains elusive. This challenge arises primarily due to the specialized use of AI by computer science experts and the difficulty in observing its adoption by other users (e.g., Alsheibani, Cheung, & Mesom, 2018; Cubric, 2020). The diversity and complexity of AI technologies mean that the impacts on solution finding discussed earlier may not uniformly apply across different technologies. However, the emergence of AIGC technologies represents a pivotal shift in this landscape. AIGC technologies have the potential to lower barriers to entry for general users, democratizing access to powerful AI tools (Cao et al., 2023; Wu et al., 2023). This increased accessibility enables a broader range of individuals, regardless of their technical expertise, to leverage AI and finally allows us to empirically examine AI technologies' influence on solution finding process of knowledge search.

Specifically, AIGC provides machine-generated solutions, which are typically more efficient than solutions provided by humans (Butcher et al., 2023; Noy & Zhang, 2023; Peng et al., 2023). Besides, AIGC can offer highly customized solutions (Baidoo-Anu & Ansah, 2023). For example, when an individual has a specific coding question, it can be challenging to find a tailored answer through generic search engines. AIGC, however, can provide more detailed and personalized responses to users. Additionally, it is important to acknowledge that the solutions offered by AIGC may not always be accurate, primarily due to the technological limitations of ChatGPT (Bang et al., 2023; Burtch et al., 2023; StackOverflow, 2022a). Finally, while machine-intelligence derived from AIGC can be stand-alone solutions, innovators tend to combine machine-intelligence with human-expertise to derive a hybrid solution, and the performance of such hybrid solutions are still unclear (e.g., Raisch & Fomina, 2024).

Understanding the potential benefits and challenges of AIGC on solution finding, we next set out to empirically explore how the introduction of a particular AIGC technology affects the solution finding of individuals.

4.3 Research Questions

We aim to explore the following specific questions based on theoretical gaps identified. Accordingly, we seek to explore these questions in a setting where problem formulation and solution finding can be separately detected. Additionally, we adopt an empirical setting where individuals can not identify the adoption of AIGC technologies, so as to avoid potential bias originated from the distrust in AI or aversion to the combination of human and machine intelligence (Turel & Kalhan, 2023; Vanneste & Puranam, 2024).

Research question 1 (validity test): Does the arrival of ChatGPT provide more potential solutions for identified problems?

Research question 2 (main test): Does the arrival of AIGC provide more accepted solutions for identified problems? Here, we further examine the quality of solutions, in addition to the sheer quantity of potential solutions.

Research question 3 (main test): Does the arrival of AIGC technologies affect the process of evaluating solutions? We further seek to explore whether the arrival of AIGC technologies demands more costs and time in evaluating the solutions.

Research question 4 (moderating effects of search experience): In this analysis, we focus on search experience as the boundary condition and seek to understand whether search experience, in both the dimension of search depth and scope, may affect the relationship between the availability of hybrid solutions and individuals' solution finding process..

4.4 Research Design And Identification Strategy

We adopt a quasi-experimental approach to investigate the influence of the arrival of AIGC technologies on the solution finding process, leveraging an exogenous shock experienced by individuals who search for new knowledge on an online technical forum, StackOverflow. Specifically, we utilize the unexpected introduction of ChatGPT, a tool powered by AIGC technologies, as an exogenous shock. In this design, our treatment group consists of active StackOverflow users who are directly impacted by ChatGPT, which allows them access to a new source of machine-generated knowledge (Burtch et al., 2023; Noy & Zhang, 2023; Peng et al., 2023). Given the universal impact of ChatGPT, we construct a pseudo control group for the adoption of the difference-in-differences research design. The pseudo control group is constituted of comparable individuals on StackOverflow from the same time period of the previous year to control for unobserved seasonal effects (Gozalo et al., 2015), and we further improve the robustness in our study with different control group construction methods. Our empirical analysis compares the solution finding processes between these two groups using the DD research design.

The arrival of ChatGPT, coupled with the context of StackOverflow, provides a unique and ideal setting for our analysis for several reasons. First, the emergence of ChatGPT serves as an abrupt and unforeseen exogenous shock. OpenAI's strategic decision to underplay ChatGPT's introduction on social media platforms contributes to the unpredictability of its market entry. As a result, accurately forecasting ChatGPT's launch timing and its subsequent influence on individuals' solution finding proved to be a significant challenge.

Second, as a leading AIGC technology, ChatGPT stands out for its ability to offer machine-generated solutions that often surpass human-provided solutions in terms of efficiency and value (Butcher et al., 2023; Noy & Zhang, 2023; Peng et al., 2023). Beyond the potential to improve search efficiency, AIGC technologies like ChatGPT can also deliver highly tailored solutions. For instance, while it is challenging for individuals to seek specific coding answers in traditional search engines (e.g., Google), ChatGPT can offer more personalized and relevant solutions to complex and technical questions (Baidoo-Anu & Ansah, 2023; Noy & Zhang, 2023).

Moreover, the introduction of ChatGPT brings a pivotal change to StackOverflow by enabling a hybrid problem solving approach that particularly suits exploratory tasks and unexplored problems (Raisch & Fomina, 2024). This shift from a human-centric search may pose significant challenges for StackOverflow and its users, since ChatGPT could provide incorrect and misleading answers, which, on the forum, nonetheless appear as generated and shared by human experts and also require "significant subject matter expertise in order to determine that the answer is actually bad" (StackOverflow, 2022a). This issue has attracted attention from StackOverflow's administration, leading them to conclude that ChatGPT could "be substantially harmful to the site and to users who are asking questions and looking for correct answers" (StackOverflow, 2022a). Accordingly, StackOverflow announces a temporary ban on all AIGC tools, including ChatGPT. However, it then becomes clear to the forum moderators that there is no effective way to detect AI-generated content unless the solution includes statements on the involvement of ChatGPT (Meta, 2023). Due to the lack of systematic and effective enforcement, the temporary ban should not contaminate the setting for our analysis, and it also suggests that those who evaluate potential solutions are most likely oblivious to whether a solution entails machine-generated knowledge.

Lastly, StackOverflow acts as one suitable context that aids in overcoming the challenge posed by the intrinsic link between problem formulation and solution finding, along with the empirical difficulties of separating these elements. (c.f., Dutt & Mitchell, 2020; Lopez-Vega et al., 2016; Zhang & Yang, 2022). Specifically, StackOverflow archives solutions for each question posted by individuals, which allows us to differentiate between the components of problem formulation and solution finding (Katila & Ahuja, 2002; Newell & Simon, 1972; Posen et al., 2018). Consequently, we believe that the unforeseen shock resulting from the introduction of ChatGPT coupled with the context of StackOverflow provides the ideal setting to investigate the role of AIGC technologies in solution finding, if a suitable pseudo control group can be constructed.

4.4 Analysis- Part 1: Validity Test

In this section, we start our analysis by validating the trend of AIGC technologies regarding their capabilities to generate more potential answers (i.e., Research question 1). This initial validation is crucial as it establishes the foundation for comprehending the role of AIGC in solution finding.

4.4.1 Sample construction

In the validity test, we begin our sample construction by identifying the treatment group that is composed of individuals on StackOverFlow who are directly affected by the arrival of ChatGPT (OpenAI, 2022). Specifically, we include all users who post at least one question in the 10 weeks preceding and after the unexpected advent of ChatGPT. Furthermore, we restrict those users who have at least one question with 500 views one year before the arrival of ChatGPT to rule out the noise from inactive users (Zhang et al., 2022). Consequently, we collect data on these active individuals over a total period of 21 weeks. This duration includes the 10 weeks prior to, the focal week of, and the 10 weeks following the introduction of ChatGPT on November 30th, 2022. In line with prior research, we concentrate on solution finding on a weekly basis, as this process is typically organized by weeks (Zhang & Yang, 2022). Moreover, given that the average time gap between two posted questions for individuals in 2022 is 9.6 weeks, our sample offers a sufficient time window to observe the impact of AIGC on problem-solving processes.

Next, to meet the requirements of the DD model, it is critical to identify a suitable control group (Wooldridge, 1999; Angrist & Pischke, 2009). However, such feat proves to be challenging, since the introduction of ChatGPT equips all individuals on StackOverflow with an universal opportunity for access to solutions generated by the integration of machine intelligence and human expertise (e.g., Medium, 2023, OpenAI, 2022). To overcome this limitation, consistent with previous studies, we craft a well-defined control group by selecting comparable individuals from the same time period from one year earlier who were not directly affected by the introduction of ChatGPTto serve as our control group (Gozalo et al., 2015).

Finally, to further strengthen the causal inference, we employ coarsened exact matching (CEM) using the Count of Questions (ln), Length of Questions (ln), Complexity of Questions (ln), and Badge-weighted Reputation (ln) as the key variables in the matching process. These variables used in CEM matching can enable us to effectively capture and control the nature of posted questions on the online forum and the capability of individuals on the online forum. Overall, we believe that this quasi-experimental design is well-suited for our research questions, and the DD research design with a matched sample mitigates potential endogeneity concerns, strengthening the identification of the causal relationship between the introduction of ChatGPT and its influence on potential solutions.

After implementing these selection criteria for both the treatment and control group, we have a panel dataset with 20,235 individual-week observations across 21 weeks for testing the impact of ChatGPT on creating potential solutions to posted questions.

4.4.2 Variables

Dependent variable. Proportion of Questions with Answers. In our context, if AIGC technologies possess the capability to generate more potential answers, it becomes inevitable that questions posted on the online forum will be more likely to receive potential answers through the integration of machine intelligence and human expertise, regardless of the quality of the answers. As the result, we construct the variable *Proportion of Questions with Answers* as the dependent variable in the validity test for each individual over the observation window. Specifically, at the individual-week level, we get this variable by calculating the ratio of questions with answers to the total number of questions posted by an individual on the online on StackOverflow.

Independent variable. Following previous studies, our study adopts the classic DD interaction term as the key explanatory variable (Wooldridge, 1999; Angrist & Pischke, 2009). The interaction term, *Treatment ×Time*, is computed as the interaction between the treatment group (individuals with access to ChatGPT) and time dummy variables.

Treatment. For *Treatment*, the variable receives the value of 1 as the sampling individual belongs to the treatment group. Otherwise, the variable receives 0 as the sampling individual is included in the control group.

*Time***.** For *Time*, a value of 1 is assigned to observation periods after the advent of ChatGPT, while a value of 0 is allocated to periods preceding ChatGPT's introduction.

Control variables. We further control for various potential sources of heterogeneity that could affect problem-solving. We first include a variety of variables to comprehensively capture the nature of question formulation, as this plays a critical role in the problem-solving process (Csaszar & Levinthal, 2016; Gavetti & Levinthal, 2000; Fleming & Sorensen, 2004; and Leiponen & Helfat, 2010). First of all, we control for the *Complexity* of posted question. This variable is particularly relevant as it captures the nature of the posted question as the complexity of the question is the primary feature of the question that may alter the possibility in obtaining potential solutions. We calculate the complexity of a posted question in two stages. As shown in equation 1, we first measure the ease of recombination. Specifically, we identify every use of the tag in previously posted questions. The sum of the number of previous uses acts as the denominator. For the numerator, we calculate the number of different tags appearing with the tag in previous questions. This term captures the ease of combining a particular tag. To create our measure of complexity for an entire posted question, we invert the average of the ease of recombination scores for the tags to which it belongs (see equation 2).

$$Observed\ ease\ recombination\ of\ tag\ i \equiv E_i = \frac{Count\ of\ tags\ previosly\ combined\ with\ tag\ i}{count\ of\ previous\ posted\ question\ in\ tagi} \quad (1)$$

$$Complexity\ of\ question\ j \equiv K_j = \frac{Count\ oftags\ on\ question\ j}{\sum_{j \in i} E_i} \quad (2)$$

where i indexes tag in the sampling and j indexes posted questions.

Additionally, we include the variable of *Code* because the inclusion or exclusion of code in a question signifies different formulation styles by the focal individual. Questions with code are expected to reflect a more specific inquiry, making the results falsifiable compared to questions without code. *Code* is quantified by the ratio of posted questions containing code to the total number of questions posted for the focal individual on a weekly basis. We control the *Length* of a posted question because the length of a question can potentially contain more detailed information, enabling responders to capture essential details for effective replies (Wang et al., 2016). *Length* is calculated by the count of words in question formulations and aggregated to the individual-week level by averaging the count of words. Further, we control for the *Scope* of the posted question and aggregate it to the individual-week level by averaging the count of tags for the posted question (Xue et al., 2023).

Besides question formulation, we also control for a variety of variables to capture individuals' activities on the online forum. Consistent with prior research, we control for the quantity of posted questions for the focal individual on a weekly base (Zhang & Yang, 2022). The *Quantity of Questions* is determined by counting the number of questions posted by the focal individual each week. Moreover, existing literature suggests that the influence of social interactions could affect question formulation within online forums (Faraj & Johson, 2011; Zhang & Yang, 2022). Consequently, in our analysis, we include the weekly activity of answering and editing. Thus, we construct the variable *Quantity of Answer* by calculating the count of answers contributed to other individuals' posted questions. We also control for a series of variables related to editing activities, including *Edit for Body*, *Edit for Tag*, and *Edit for Title*, by measuring the count of these activities respectively. Furthermore, the discovery of solutions might be influenced by the visibility of other users on the online forum. Increased exposure to other users could enhance the likelihood of finding potential solutions (Sun & Zhu, 2013; Zhang & Yang, 2022). Therefore, we incorporate the variable of *Views* as the control variable. Specifically, the variable is aggregated to the individual and week level by averaging the count of views for each question posted by the focal individual on a weekly basis.

We also control for the *Reputation* of individuals on the online forum by calculating the badge-weighted reputation using tag badges. StackOverflow assigns gold, silver, and bronze badges to individuals as symbols of honor, which can be used to capture their reputation. Specifically, we follow the equation provided by the forum, which assigns different weights to each badge to determine the overall reputation.

$$Reputation_{it} = Bronze\ badge_{it} + 4 \times Silver\ badge_{it} + 10 \times Gold\ badge_{it} \tag{3}$$

where i indexes individuals in the sampling and t indexes week.

Considering the skewed distribution of these variables, we apply natural logarithm transformations to these variables to mitigate the potential impact of skewness. Descriptive statistics and correlations of the variables are shown in Table 1A.

------ Insert Table 1A about here ------

4.4.3 Estimation approach

Following previous research, we employ the DD model with a matched sample to validate the trend of AIGC technologies in terms of their capacity to produce more potential answers. (Wooldridge, 1999; Angrist & Pischke, 2009). Given that the dependent variable is a continuous variable, we employ the OLS model with both week and individual fixed effects and cluster the standard errors at the individual level, with the following specifications.

$$Proportion\ of\ Questions\ with\ Answers_{it} = \beta_0 + \beta_1 \text{Treatment}_{\ i} \text{ x After} + \theta_{it} + \varepsilon_{it} \qquad (4)$$

where i indexes individuals in the sampling and t indexes week. We mainly focus on the coefficient of interaction term β_1\to identify the change of dependent variable for the individuals in the treatment group compared to those individuals in the control group after the advent of ChatGPT. θ_{it} acts the vector of control variables and $\varepsilon_{it}$is the error term.

4.4.4 Results

To establish the validity of our research design, we first test the comparability assumption as outlined by Angrist and Pischke (2009). This begins by examining the covariate balance between the treated and control groups before ChatGPT's arrival. The non-significant differences in the means of control variables across all hypotheses suggest that the two groups are comparably matched. We then evaluate the parallel trend assumption. According to Figure 1, we observe no significant differences between the two groups prior to the introduction of ChatGPT. This observation validates the critical assumption for the DD model, reinforcing its applicability in this context.

Table 2 shows the results of our validity test, aimed at evaluating whether the arrival of ChatGPT creates more potential answers. Model 1 reveals that the positive and significant coefficient of the DD term ($\beta_1 = 0.033, p = 0.004$), which suggests that the advent of AIGC technologies, as epitomized by ChatGPT, plays a pivotal role in creating more potential answers. ChatGPT, with its advanced natural language processing capabilities, stands out for its ability to efficiently facilitate the generation of solutions through interactive conversations (OpenAI, 2022). The introduction of ChatGPT significantly lowers the barriers to becoming a domain expert, thereby augmenting the pool of individuals with expert-level knowledge in specific fields. Consequently, this expansion of domain experts leads to an increase in the volume of potential solutions generated by the integration of machine intelligence and human expertise, underscoring the transformative impact of AIGC technologies.

------ Insert Table 2 about here ------

4.5 Analysis- Part 2: Main Test

In the previous section, we have established that integrating AIGC technologies with human expertise can significantly generate more potential solutions. However, whether these potential answers can effectively transform into accepted solutions remains ambiguous, and the impact of AIGC technologies on the process of obtaining accepted answers is still unclear. In the main test, we delve deeper to further address these questions (i.e., Research question 2 and 3).

4.5.1 Sample construction

In the main analysis, we also utilize the activity logs from StackOverflow as our primary data source, which allows us to capture the solution's quality and track the solution finding procedure. On StackOverflow, one and only one answer to a question will be selected as the accepted solution to that question, and we hence use this accepted solution in determining the quality of solutions. Specifically, to explore the role of AIGC technologies on the proportion of questions that obtain accepted solutions, we use identical data sampling in the validity test, which spans 21 weeks in total, consisting of the 10 weeks before, the week of, and the 10 weeks after the introduction of ChatGPT (OpenAI, 2022).

Subsequently, we closely examine the process of attaining satisfactory solutions. As a result, it becomes important to refine our data sampling in order to more precisely evaluate the role of AIGC technologies in securing accepted solutions. Here, we reshape our treatment group by including all users who not only post on the online forum but also receive accepted solutions in both the pre-and post-advent of ChatGPT. This specific inclusion criterion ensures a focused examination of individuals who actively participate in discussions and experience success in solution finding. Likewise, we refine our sampling by only including those individuals who have at least one question with 500 views on the online forum one year before the advent of ChatGPT (Zhang et al., 2022). Next, we adopt the same methodology in the validity test to construct a comparable control group, which involves collecting data on individuals who have posted at least one question and received at least one satisfactory solution in the same time window but one year prior (Gozalo et al., 2015). Likewise, we employ CEM matching using Count of Questions (ln), Length of Questions (ln), Complexity of Questions (ln), and Badge-weighted Reputation (ln), which is as same as variables in sample construction for validity test to capture the nature of posted questions and capabilities of individuals on StackOverflow to reinforce the balance between our treatment and control group before our regression analysis.

We assemble an unbalanced panel dataset according to the defined selection criteria for both the treatment and control groups. This dataset includes 17,953 individual observations over a period of 21 weeks. It serves to examine the influence of ChatGPT on the process of obtaining satisfactory solutions.

4.5.2 Variables

Dependent variable. Proportion of Question with Accepted Solutions. While the presence of solutions to a question is a necessary condition for identifying an accepted solution, it is not a sufficient condition for actually obtaining a satisfactory solution (Greve, 2003). Successfully obtaining a satisfactory solution depends significantly on the quality of the solution itself. In our context, the decision to accept a solution on StackOverflow serves as an indicator of the solution’s satisfactoriness. This choice reflects the individual's assessment of the solution's quality, with higher quality solutions being more likely to meet the requirements and thus be accepted (StackOverflow, 2008). Therefore, we select the *Proportion of Question with Accepted Solutions* as the dependent variable to test the question of whether the introduction of AIGC technologies facilitates obtaining accepted solutions. We aggregate this variable to the individual-week level by calculating the ratio of questions with accepted answers to the total number of questions posted by the focal individual on the online forum on a weekly basis.

Time to Obtain Accepted Solutions. In problem-solving, time is one of the most critical and significant costs in the procedure of selecting the appropriate solution among potential answers (e.g., Raisch & Fomina, 2024). The longer duration required to secure an accepted solution signifies greater expenditure of efforts. Within our context, the process of obtaining an accepted solution on StackOverflow starts with the posting of a question on an online platform, exposing individuals on the online forum to a variety of potential answers. Individuals on the online forum spend time to thoroughly review these potential solutions, determining their suitability in addressing the posted query. This step is essential for deciding to adopt an answer as the accepted solution, underscoring the significant cost of time in finding a satisfactory solution. Hence, we construct the variable representing the time taken to receive an accepted solution as the proxy for the cost of evaluating the potential solutions. Specifically, this variable is measured by the time elapsed between the appearance of the first answer and the moment when an individual decides to accept one of the solutions after reviews and evaluations. We aggregate to individual-week level by averaging the time used to obtain an accepted solution for the focal individual on the online forum on a weekly basis. To address the skewness in the distribution of the *Time to Obtain Accepted Solutions*, we utilize the natural logarithm transformation as an effective solution.

Independent variable. We adopt the same explanatory variables as in the validity test for the DD analysis.

Control variables. In the main test, we account for a range of potential heterogeneity factors that could impact problem-solving by including the following control variables. Specifically, we incorporate the same control variables in the validity test to eliminate the possibility of time-varying heterogeneities among individuals.

Furthermore, when examining the role of AIGC technologies on the probability of obtaining an accepted solution and the time required to obtain a satisfactory solution, we incorporate the length of *Chains to obtain the accepted solution* at the individual-week level as a control variable to capture the process of problemistic searching (Cyert & March, 1963; March, 1991; Posen et al., 2018). This captures the process in reaching satisfactory solutions. To address the skewed distribution of *Chains and Time to Obtain Accepted Solutions*, we employ the natural logarithm transformation as a corrective measure.

Variables used to examine the impact of ChatGPT on the probability of obtaining an accepted solution can be found in Table 1A. Meanwhile, Table 1B displays the variables in the datasets used to investigate the role of AIGC technologies in determining the quality of solutions and the process of obtaining accepted solutions.

------ Insert Table 1A about here ------

------ Insert Table 1B about here ------

4.5.3 Estimation approach

Following the estimation approach in the validity test, we adopt the same fixed effects models to estimate the role of the introduction of ChatGPT on the proportion of questions with accepted solutions and the time to obtain accepted solutions. We proceed to assess the parallel trend assumption, as depicted in Figures 1B and 1C. On these graphs, it is evident that there is no significant alteration in the trend preceding the advent of ChatGPT. This finding substantiates the essential assumption underlying the DD research design.

4.5.4 Results

The results for the main tests are shown in Table 3. Model 1 focuses on testing whether the emergence of ChatGPT affects the proportion of questions that obtain accepted solutions. The absence of statistical significance for the coefficient of the DD term ($\beta_1 = 0.012, p = 0.333$) suggests that the introduction of ChatGPT does not exert a significant influence on obtaining satisfactory solutions, although ChatGPT, as AIGC technologies, create more potential answers for individuals on the online forum. Our findings reveal that although AIGC technologies have advantages in terms of providing the hybrid solution finding, lowering the barriers to becoming a domain expert and generating more potential solutions, their effectiveness in consistently yielding high-quality solutions is not uniform. Simply put, the surge in potential solutions does not necessarily translate into an increase in accepted solutions. This limitation can be attributed to inherent technological deficiencies, such as the generation of irrelevant information or incorrect answers.

Model 2 in Table 3 assesses the impact of ChatGPT's emergence on the time required to achieve a satisfactory solution. The positive and significant coefficient for the DD terms ($\beta_1 = 0.087, p = 0.000$) indicates that the emergence of ChatGPT extends the time needed to evaluate and select satisfactory solutions. Our findings suggest that while ChatGPT introduces more potential answers to posted questions, it also imposes significant least two challenges for individuals on the online forum. First, AIGC generates a larger pool of potential solutions, necessitating increased effort to evaluate and select the most suitable ones (i.e., increase the noise for individuals on the online forum). Furthermore, it increases solution alternatives (especially to questions that would not have obtained a solution) without necessarily improving their usefulness, thereby extending the time required to verify the correctness of the solutions and to await more responses to compare with (i.e., uncertain quality of potential answers).

------ Insert Table 3 about here ------

4.6 Analysis- Part 3: Search Experience as the Boundary Condition

In this section, we conduct additional analyses to explore individuals'heterogeneous search experience on the relationship between the introduction of ChatGPT and solution findings. Specifically, we focus on two dimensions—search depth and search scope (Katila &

Ahuja, 2022). These two dimensions can be regarded as proxies for individuals' experience and their abilities to assess solutions across two distinct aspects. On one hand, deep search has its merits in quickly identifying relevant knowledge and effectively evaluating potential solutions. Deep search taps into existing knowledge repeatedly, allowing individuals to leverage their knowledge and experience in familiar domains. Accordingly, high search depth can afford swift and effective solution evaluation, as deep search in known knowledge domains may allow individuals to recognize reliable solutions more efficiently (Berchicci et al., 2019; Katila & Ahuja, 2002; Leiponen & Helfat, 2010). On the other hand, individuals are subject to higher uncertainties when attempting to search broadly that involve unfamiliar knowledge, which can create barriers to assessing solutions and lead to solutions with lower average returns (Cyert & March, 1963; Fleming, 2001; March, 1991). As such, prolonged search, escalating costs, and additional difficulties in finding solutions may occur, as a result of the increased likelihood of unexpected search failure associated with broad knowledge search (Benner & Tushman, 2002). Consequently, in our context, past search direction of individuals would affect how ChatGPT may affect individuals' solution finding, given that individuals' search directions can affect whether and how efficiently they could evaluate solutions augmented/provided by ChatGPT and posted by answer providers.

4.6.1 Subsample construction

We focus on the variations in search depth and scope as potential boundary conditions for assessing the role of AIGC technologies in individuals' solution finding. To better investigate the influence of AIGC on solution findings, we perform subsample analysis based on the median values of search depth and search scope.

Regarding search depth, previous studies suggest that the frequency of an individual's searches within a familiar domain is directly proportional to the depth of their exploration in that area (Katila & Ahuja, 2002). To calculate the first variable, *Search Depth*, we follow a two-step process. We first we calculate the frequency of tag usage for each individual at the tag level, accumulating this frequency from the registration of their StackOverflow account. Then, this data is aggregated to the individual-week level by averaging the specific and cumulative frequency of tags used by each individual in a particular week.

$$Search\ Depth_{it} = \frac{\sum_j Cumulative\ Tag\ Usage\ Frequency_{jit}}{Total\ Tag\ Count_{it}} \quad (5)$$

where $Cumulative\ Tag\ Usage\ Frequency_{jit}$ indicates the individual-specific cumulative tag usage frequency of a tag *j* that is used by individual *i* in a given week *t*, and $Total\ Tag\ Count_{it}$ indicates the total number of tags used by individual *i* in a given week *t*.

Search Scope assesses an individual's engagement and expertise across various domains. To capture an individual's search breadth that expands in unfamiliar domains, we calculate the ratio of new tags (tags not previously explored) to the cumulative count of all tags explored in the focal week. A higher value of the search scope ratio indicates that individuals are more likely to expose themselves to uncertain environments and lack relative domain knowledge. Conversely, a lower value suggests that individuals are operating within a more familiar domain, indicating a higher level of domain knowledge.

4.6.2 Results

In Table 4, we explore the advent of ChatGPT on individual's solution finding, considering different levels of search depth (subsample separated at the median of *Search Depth*). We employ the same regression model as before. Models 1A and 2A focus on a subsample characterized by a relatively high search depth. In contrast, models 1B and 2B examine individuals with a relatively low search depth.

The coefficients of the DD terms in Models 1A and 1B suggest that the influence of the arrival of ChatGPT on an individual's obtaining accepted solutions is not significant, as individuals have different levels of search depth ($\beta_1 = 0.009, p = 0.635$ in Model 1A, $\beta_1 = 0.016, p = 0.404$ in Model 1B). In other word, these results indicate that search depth does not yield a significant impact on the role of AIGC technologies in obtaining satisfactory solutions.

Here, we shift our focus to the time to obtain an accepted solution. Model 2A shows a positive and significant DD term ($\beta_1 = 0.136, p = 0.000$), while Model 2B does not yield significant results ($\beta_1 = 0.032, p = 0.334$). This suggests that those domain experts tend to require more time to evaluate the solutions provided by the integration of AIGC technologies. This delay could be attributed to the lack of precision in solutions provided by ChatGPT, compelling these knowledgeable individuals to engage more deeply with contributors to refine and arrive at suitable solutions.

Our empirical research underscores the intrinsic limitations of AIGC technologies (Aisnakeoil, 2022), while simultaneously emphasizing the pivotal role of human involvement in the process of interacting with machines powered by AIGC technologies (Raish & Fomina, 2024). Specifically, while AIGC technologies offer innovative solutions, their effectiveness is not uniform across all user groups, particularly those with varied levels of contextual understanding. For individuals lacking domain-specific expertise, technologies like ChatGPT can significantly reduce the learning curve, making it easier to acquire expertise. However, for seasoned professionals, AIGC may offer less pronounced advantages, potentially even introducing new challenges that need to be navigated.

------ Insert Table 4 about here ------

With regard to *Search Scope*, we follow the same approach by splitting the sample at the median value (i.e., high vs. low level of search scope). In Table 5, Models 1A and 2A adopt DD research design on a sub-sample of individuals with a relatively high search scope, while Models 1B and 2B focus on individuals with a relatively low search. The coefficient of the DD term in Model 1A is positive and significant ($\beta_1 = 0.034, p = 0.070$). However, the coefficient of the DD term in Model 1B is not significant ($\beta_1 = 0.004, p = 0.8474$).

Combining the coefficients of DD terms, these findings suggest that individuals who explore knowledge in unfamiliar domains are more likely to benefit from AIGC technologies. These technologies decrease the cost and effort required to become a domain expert, while they have a limited role for individuals with existing domain knowledge. Moving on to Models 2A and 2B, which examine the impact of different levels of search scope on the relationship between ChatGPT's introduction and the time taken to obtain an accepted solution, we find that the coefficient of the DD term is positive and significant in model 2A ($\beta_1 = 0.127, p = 0.000$) but not significant for Model 2B ($\beta_1 = -0.024, p = 0.521$). These results emphasize the crucial role of human intelligence in evaluating solutions generated through the combination of human and machine intelligence. To accurately assess potential answers, more time and effort are required for evaluation.

The empirical results align with theoretical discussions on the interaction between humans and machines in the AIGC era. They provide evidence that the process of solution finding is largely constrained by human's ability in evaluating solutions (Raish & Fomina, 2023). When individuals are exposed to more uncertain knowledge domains (i.e., higher scope), their lack of related contextual understanding increases the cost of obtaining the accepted solution (Cyert & March, 1963; Fleming, 2001; March, 1991). In conclusion, this continued exploration is essential for effectively harnessing the complementary strengths of both human and AI capabilities in knowledge search and solution finding processes.

------ Insert Table 5 about here ------

4.7 Robustness Check

To ensure the robustness of effects in the previous tests, we design and conduct several robustness checks. These checks are performed to confirm that the effects remained consistent across different pseudo control groups and varying time window lengths.

Furthermore, we aimed to verify that the observed effects were indeed triggered by the exogenous shock of ChatGPT's arrival.

4.7.1 Alternative control groups

In this study, it is challenging to identify the control group at the same time window according to the traditional differences-in-differences design, since the introduction of ChatGPT affords all individuals on the online forum with access to solutions generated by the combination of machine intelligence and human intelligence. Thus, drawing from the main idea of a differences-in-differences design, we craft a pseudo control group consisting of individuals who are not directly influenced by the introduction of ChatGPT in one year before. Although this identification strategy allows us to approximate the causality of ChatGPT's introduction on solution findings, it is still limited as the selection of the pseudo control group is rather arbitrary. Therefore, it is crucial to test whether these effects remain robust when alternative pseudo control groups are selected.

Specifically, we include comparable individuals who were not directly affected by the introduction of ChatGPT two years prior and those not affected one and two years prior as alternative control groups. Following the same identification and empirical strategy, we perform CEM matching by using the Count of Questions (ln), Length of Questions (ln), Complexity of Questions (ln), and Badge-weighted Reputation (ln) to balance the sampling individuals between treatment and control group. We apply the same control variables in the previous tests and re-run the differences-in-differences regression in the robustness check on the alternative selection of the control group.

For the robustness check on the validity test, models 1A and 1B in Table 6 represent results for different selections of the control group. The consistently positive and significant DD terms in model 1A and 1B in Table 6 suggest that the introduction of ChatGPT can generate more potential answers ($\beta_1 = 0.021, p = 0.060$ in Model 1A and $\beta_1 = 0.028, p = 0.002$ in Model 1B). In other word, these results ensure the robustness of the validity test.

Next, to examine the robustness of our main test, we re-run the regression by considering alternative control groups. The non-significant coefficients of DD terms in Model 1A and 1B in Table 7 suggest that the introduction of ChatGPT does not necessarily transfer potential answers into accepted solutions, though AIGC creates more potential solutions ($\beta_1 = 0.007, p = 0.587$ in Model 1A and $\beta_1 = 0.009, p = 0.390$ in Model 1B). Likewise, the consistently positive and significant DD term in Model 2A and 2B in Table 7 indicate the robustness of positive effects of the introduction of ChatGPT on time to obtain accepted solutions ($\beta_1 = 0.106, p = 0.008$ in Model 2A and $\beta_1 = 0.085, p = 0.004$ in Model 2B).

Further, we check the robustness of the effects of boundary conditions. Regarding the boundary condition of search depth, the lack of significant rates of coefficients of DD terms in Models 1A, 1B, 2A, and 2B in Table 8A suggest that the arrival of ChatGPT does not significantly impact the proportion of questions with accepted solutions across different levels of search depth, which is consistent with previous tests.

Results in Table 8B indicate the boundary condition of search depth on the role of AIGC technologies and time to obtain accepted solution. Specifically, Model 1A and 2A refer to a sub-sample of individuals with high search depth, and Model 1B and 2B represent a sub-sample of individuals with low search depth. The coefficients of DD terms are not significant in Model 1A and 2A ($\beta_1 = 0.030, p = 0.564$ in Model 1A; $\beta_1 = 0.026, p = 0.513$ in model 2A), while coefficients of DD terms are positive and significant in Model 1B and 2B ($\beta_1 = 0.164, p = 0.008$ in Model 1B; $\beta_1 = 0.138, p = 0.002$ in Model 2B). These results provide evidence of robustness effects that the positive effect on time to obtain accepted solution is only significant for those individuals with relatively low search depth.

Shift the focus to the boundary condition of search scope. Models 1A and 2A in Table 9A refer to a sub-sample of individuals with high search scope, and Model 1B and 2B indicate the sub-sample of individuals with a relatively low search scope. The coefficient of DD term is positive and significant in Model 1A, and the coefficient of DD term in model 2A is positive and significant ($\beta_1 = 0.045, p = 0.020$ in Model 1A and $\beta_1 = -0.013, p = 0.512$ in Model 2A). Conversely, the coefficients of DD terms are not significant in Model 1B and 2B. These results suggest that AIGC technologies benefit those individuals with more explorations under unexplored areas.

Models 1A, 1B, 2A, and 2B in Table 9B test the robustness of the boundary condition of search scope on the relationship between the arrival of ChatGPT on time to obtain accepted solutions. The coefficients of DD terms in Model 1A and 2A ($\beta_1 = 0.108, p = 0.085$ in Model 1A and $\beta_1 = 0.133, p = 0.04$ in Model 2A) are positive and significant, but the coefficients of DD terms in Model 1B and 2B are not significant. Combined with these results, these analyses support the robust positive effect of AIGC technologies on time to obtain accepted solutions for those individuals who explore in unfamiliar domains.

4.7.2 Alternative observation windows

In previous tests, the treatment and pseudo control groups were constrained to individuals who posted at least one question 10 weeks before and after the arrival of ChatGPT in 2022 and the same time period one year prior. Our results can be biased due to the selection of the time window for constructing the treatment and control groups. Thus, it is crucial to test whether these results are affected by the selection of time window length. Specifically, we selected 8-week and 12-week periods before and after the arrival of ChatGPT as alternative time window lengths.

To examine the impact of ChatGPT's arrival on the proportion of questions with potential answers and accepted solutions, as well as their corresponding boundary conditions, we identified the treated group by including individuals who posted at least one question in both the 8-week (or 12-week) periods before and after ChatGPT's arrival. Likewise, we used the same identification strategy for the pseudo control group, selecting individuals who were not directly affected by the introduction of ChatGPT in the year prior. Additionally, we included individuals who posted at least one question in the 8-week (or 12-week) periods before and after ChatGPT's arrival and those who raise one question with 500 views in the year had at least prior, to exclude non-active users. We applied CEM matching using the count of questions (ln), length of questions (ln), complexity of questions (ln), and badge-weighted reputation (ln). Likewise, we perform a differences-in-differences model to estimate the impact of ChatGPT's arrival on the proportion of questions with potential answers and accepted solutions.

For the validity test, Models 1C and 1D in Table 6 represent different selections of time window lengths (i.e., 8-week and 12-week periods). The positive and significant coefficients of DD terms in models 1C and 1D support the robustness of the effects of the introduction of ChatGPT on the proportion of questions with potential answers ($\beta_1 = 0.034, p = 0.005$ in Model 1C and $\beta_1 = 0.038, p = 0.000$ in Model 1D).

For the main test, in Table 7, Models 1C and 1D are used to test the robustness of the introduction of ChatGPT on the proportion of questions with accepted solutions, and Models 2C and 2D examine the robustness of the effects of the arrival of ChatGPT on the time to evaluate satisfactory solutions. The non-significant DD terms in models 1C and 1D further support the idea that the introduction of ChatGPT does not necessarily lead to satisfactory solutions, although ChatGPT, as an AIGC technology, creates more potential solutions generated by the combination of human and machine intelligence. The consistently positive and significant coefficients of DD terms in models 2C and 2D suggest the robustness of the effect that the introduction of ChatGPT requires more time to evaluate and obtain accepted solutions ($\beta_1 = 0.091, p = 0.038$ in Model 2C; $\beta_1 = 0.082, p = 0.002$ in Model 2D). These results provide evidence for the robustness effect that AIGC technologies require more time to obtain the accepted solution.

Similarly, we also test the robustness of boundary conditions. For search depth, Models 3A and 3B in Table 8A examine the robustness by including an 8-week period, and Models 4A and 4B test the robustness by including a 12-week period. The non-significant coefficients of the DD terms support the idea that different levels of search depth do not moderate the relationship between the introduction of ChatGPT and the proportion of questions with satisfactory solutions. In Table 8B, models 3A, 3B, 4A, and 4B represent different sub-samples with different time window lengths (i.e., 8-week and 12-week periods) to test the robustness of the role of search depth on the relationship between the introduction of ChatGPT on time to obtain accepted solution. Model 3A and 4A refer to the subsample of individuals with high search depth, and model 3B and 4B indicate the sub-sample of individuals with low search depth. The coefficients of DD terms in Model 3A and 4A is not significant, while model 3B and 4B are positive and significant ($\beta_1 = 0.194, p = 0.003$ in Model 3B and $\beta_1 = 0.138, p = 0.000$ in Model 4B). These results validate the robustness of effects that the positive role of AIGC technologies is only significant for that individual with a relatively low search depth.

Table 9A addresses the robustness of the role of search scope on the relationship between AIGC technologies and time to evaluate solutions. Specifically, Model 3A and 4A refer to the sub-sample with high search scope (i.e., more explorations under the new tag) for different time window lengths; the coefficients of DD terms in Model 3A and 4A are positive and significant. However, the coefficients of the DD term in Models 3B and 4B, for the sub-sample of those individuals with a low search scope, are not significant. These results suggest that the robust effect of the introduction of ChatGPT on the proportion of obtaining accepted solution for those individuals with more explorations under new tags. In Table 9B, models 3A, 3B, 4A, and 4B are used to test the robustness of the effect of AIGC technologies on time to obtain accepted solutions. Specifically, Model 3A and 4A include the sub-sample of those individuals with high search scope, and the coefficient of DD term is positive and significant. Alternatively, Model 3B and 4B include the sub-sample of those individuals with low search scope, the coefficients of DD terms are not significant. These results support the robustness of effects of ChatGPT on time to obtain accepted solution is only significant for those individuals with high search scope.

4.7.3 Exogenous shock of arrival of ChatGPT

We test the robustness of these effects to determine if they are influenced by the arrival of ChatGPT rather than by the passage of time. We re-run the differences-in-differences regression between two alternative control groups: individuals who were not directly affected by the introduction of ChatGPT one year prior (labeled as control group C1) and two years prior (labeled as control group C2). Similarly, we perform CEM matching using the Count of Questions (ln), Length of Questions (ln), Complexity of Questions (ln), and Badge-weighted Reputation (ln) to reinforce the causal inference of whether the passage of time drives the changes in the dependent variables we are concerned with.

The primary dependent variables are similar to those in the validity and main tests. Following the differences-in-differences design, the treatment and time dummy variables are the primary independent variables. Individuals in C1 after CEM matching are assigned a value of 1, while individuals in C2 after CEM matching are assigned a value of 0. For the post dummy variable, the weeks after November 30th for C1 and C2 are assigned a value of 1. We use the same control variables as in the validity test and main test.

In Table 4.2.2, the coefficients of the DD terms are not significant in models 1 to 3. These results provide evidence that the passage of time does not drive the changes in the dependent variables we are interested in ($\beta_1 = 0.005, p = 0.510$ in Model 1; $\beta_1 = 0.006, p = 0.476$ in Model 2; $\beta_1 = 0.047, p = 0.269$ in Mode 3). In other words, we confirm that the arrival of ChatGPT acts as an exogenous shock that drives the change in problem-solving.

------ Insert Table 6 about here ------

------ Insert Table 7 about here ------

------ Insert Table 8A about here ------

------ Insert Table 8B about here ------

------ Insert Table 9A about here ------

------ Insert Table 9B about here ------

------ Insert Table 10 about here ------

4.8 Discussion

4.8.1 Research contribution

Exploring the research question of how AI-supported intelligence affects the solution finding process, we make several theoretical contributions. First, we build upon existing research that has extensively examined the knowledge search process. Previous studies have analyzed the process as a whole, dissected it into two critical components (problem formulation and solution finding), explored the interplay between these components, and lately studied problem formulation as a standalone component (Baer et al., 2012; Dutt & Mitchell, 2020; Gavetti & Levinthal, 2000; Knudsen & Levinthal, 2007; Kneeland et al., 2020; Lopez-Vega et al., 2016; Nickerson et al., 2012; Zhang & Yang, 2022). However, the solution finding process, as an independent process of knowledge search, remains relatively underexplored. Our work addresses this gap by focusing exclusively on solution finding, and we leverage the distinct question-answer structure of our data to empirically investigate the relationship between technological advancements in AIGC and the identification of appropriate solutions, marking one of the first such endeavors in this field. This approach complements previous studies that predominantly relied on patent or product data (Katila & Ahuja, 2002), where distinguishing solution finding from problem formulation is challenging.

Moreover, knowledge search is shaped by diverse environmental factors (Argyres & Silverman, 2004; Dutt & Mitchell, 2020; Laursen & Salter, 2014; Morandi Stagni et al., 2021), and hence the process of knowledge search is also inevitably influenced by these factors. Acknowledging the substantial impact of these external factors, scholars have investigated factors shaping problem formulation, yet similar in-depth research on solution finding is lacking (Baer et al., 2012; Newell & Simon, 1972; Zhang & Yang, 2022). Our study fills this gap by examining how a particular technological change—the evolution of AIGC technologies—can transform the solution finding process through machine intelligence. We present evidence demonstrating that while AIGC technologies enhance access to potential machine-based solutions, they do not necessarily simplify the solution finding process for individuals.

Additionally, we contribute to the AI in management literature. A topic of the research has focused on the interaction between AI technologies and knowledge workers. A growing literature has investigated various dimensions of this interaction, including AI's impact on worker performance (Boyaci et al., 2023; Kim et al., 2023; Man Tang et al., 2022), the dynamics of AI and worker interaction and their adaptation to AI (Allen & Choudhury, 2022; Anthony, 2021; Fügener et al., 2021; Lebovitz et al., 2022; Lysyakov & Viswanathan, 2023; Wang et al., 2023), AI's potential to augment or replace human workers (Balasubramanian et al., 2022; Choudhury et al., 2020; de Vericourt & Gurkan, 2023; Gaessler & Piezunka, 2023; Krakowski et al., 2022; Raisch & Krakowski, 2021; Xue et al., 2022), and finally knowledge workers' sentiments toward machine intelligence (Turel & Kalhan, 2023 ; Vanneste & Puranam, 2024). However, the specific ways in which AI technologies shape the knowledge search processes of individuals is still a largely unexplored area. Our research addresses this gap by presenting evidence from a particular AI technology and its effect on individuals' solution finding. Specifically, we suggest that human intelligence is still vital, at least in the current stage, in evaluating solutions supported by machine intelligence. And such a result is not the result of biases created by human aversion against machines, given that individuals cannot clearly identify solutions supported by the AIGC technology (Turel & Kalhan, 2023; Vanneste & Puranam, 2024). This contributes to the broader discussion on how individuals adapt to AI technologies, enhancing our understanding of the intersection between AI and knowledge management.

Finally, we join the ongoing discussion of human and AI complementarity (e.g., Raish & Fomina, 2023; Choudury et al., 2020; Kesavan & Kushwaha, 2020; Tong et al., 2021; Xue et al., 2022). Specifically, our findings indicate that, at least in the current stage, human evaluation remains a crucial component of the solution finding process, despite the potential for innovative and creative solutions offered by integrating machine intelligence and human intelligence. Moreover, hybrid solutions that integrate machine-intelligence with human expertise may not be superior, as human expertise may be biased. However, as noted in our discussion of limitations, we acknowledge that ongoing technological advancements may alter the necessity for human involvement in evaluation and could potentially transform the entire landscape of knowledge search.

4.8.2 Limitation and future research

This study, while contributing valuable insights, is subject to several limitations that pave the way for future research. First, one key limitation of our study is its generalizability. As we have explored, AIGC technologies represent a distinct subset of AI technologies, and their influence on the solution finding processes of different individuals, each seeking new knowledge in varied contexts, can differ significantly, and sometimes even be at odds. This limitation is further compounded by the rapid and ongoing evolution within AIGC technologies, which may limit the applicability of our findings over time. For instance, the initial version of ChatGPT, released in November 2022, was built on a variant of the GPT-3 that was originally introduced in June 2020. It swiftly transitioned to using GPT-4 in 2023, where future iterations are expected to continue this trend of incorporating advanced generations of the GPT engine (Forbes, 2023). Each iteration of ChatGPT, although beyond the observation window of our current study, has the potential to offer more refined and effective solutions, potentially rendering our current observations less relevant or even obsolete. Therefore, we recommend exercising caution when applying our findings, especially considering the dynamic and rapidly evolving nature of AIGC technologies.

In addition, our focus on solution finding means we have not fully explored the influence of AIGC on product-level solutions and problem-solving. GitHub, as a platform, presents an ideal environment for investigating how the application of tools like ChatGPT impacts problem-solving processes at the product level. Future research in this area could provide deeper insights into the role of AIGC in enhancing product development and innovation.

Finally, the study's methodology predominantly relies on quantitative data, which might overlook the nuanced, qualitative aspects of how individuals interact with and perceive ChatGPT. The quantitative approach provides valuable insights into behavioral patterns and general trends but may not capture the subjective experiences, attitudes, and perceptions of individual individuals. These qualitative dimensions could offer a deeper understanding of the cognitive and emotional factors influencing the adoption and utilization of ChatGPT. Therefore, future research could benefit from incorporating qualitative methodologies, such as interviews or case studies, to gain a more holistic view of ChatGPT's impact on the individual community. This approach could reveal insights into personal experiences, decision-making processes, and the cultural context surrounding the use of AI tools in problem-solving.

4.9 Conclusions

The advent of AIGC technologies marks a pivotal change in problem-solving activities and the approach to knowledge search, potentially transforming the solution finding process. Our exploration shows that, in response to the introduction of ChatGPT, a LLM based Q&A query AIGC technology, the number of answers for questions posted on StackOverflow increase after controlling for heterogeneous problem formulation considerations. However, this increase in the volume of answers does not correlate with a higher likelihood of finding satisfactory solutions. Intriguingly, both the time taken to arrive at a solution and the follow-up discussions after an accepted answer have shown an increase. Furthermore, a crucial aspect of this phenomenon is the role of an individual's evaluation capability, which introduces heterogeneity in these findings. These results jointly suggest that despite the high volume of hybrid solutions generated by integrating AI-generated knowledge and human knowledge, their effectiveness is not necessarily superior to that of crowdsourced solutions from human intelligence. These hybrid solutions demand similar, if not greater, levels of complementary evaluation by individuals in their quest for knowledge. Our study contributes to the expanding body of literature on knowledge search and the burgeoning field of AI in management research. We show that while AI technologies hold the potential to revolutionize knowledge search, the solutions they provide, particularly those from still-evolving technologies, require careful scrutiny and complementary evaluation by either humans or machines. Such findings are crucial for understanding the dynamics of AI-assisted problem solving and for guiding future innovations in AI technology deployment in knowledge-intensive domains.

4.10 References

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4.11 Tables

Table. Summary Statistics

Table 1A. Summary Statistics And Correlation: Initial Sample

	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Proportion of Question with Answers(1)	0.73	0.41	0	1	1														
Proportion of Question with Accepted Solutions (2)	0.44	0.46	0	1	0.535	1													
Quantity of Question(ln) (3)	0.85	0.29	0.69	3	0.02	0.031	1												
Quantity of Answer(ln) (4)	0.15	0.37	0	3.66	0.109	0.061	0.132	1											
View (ln) (5)	4.84	1.28	1.79	11.51	0.28	0.156	0.058	0.063	1										
Length(ln) (6)	5.33	0.92	1.95	9.67	-0.017	0.001	0.106	0.033	0.08	1									
Code (ln) (7)	0.62	0.2	0	0.69	0.048	0.071	0.058	0.034	0.035	0.336	1								
Edit for Body (ln) (8)	0.39	0.57	0	5.79	0.048	0.057	0.35	0.319	0.09	0.199	0.11	1							
Edit for Tag (ln) (9)	0.04	0.19	0	4.13	0.005	0.018	0.133	0.163	0.036	0.028	0.019	0.313	1						
Edit for Title (ln) (10)	0.06	0.22	0	4.03	0.019	0.023	0.176	0.157	0.041	0.045	0.024	0.368	0.318	1					
Reputation (ln) (11)	0.3	0.57	0	4.72	0.026	0.043	0.129	0.103	0.042	-0.001	0.029	0.122	0.054	0.067	1				
Scope(ln) (12)	1.35	0.31	0.69	1.79	-0.006	-0.013	0.01	0.035	0.159	0.185	0.04	0.059	0.101	0.046	0.003	1			
Complexity (ln)(13)	1.24	0.07	0.62	1.43	-0.076	-0.074	-0.011	0.011	0.064	0.091	0.004	0.021	0.039	0.016	-0.006	0.526	1		
Search Depth (14)	2.69	1.69	1	38.67	0.027	0.042	0.219	-0.033	-0.07	0.095	0.084	0.091	0.038	0.031	0.109	-0.055	-0.092	1	
Search Scope (15)	0.07	0.15	0	1	0.055	0.011	0.019	-0.006	0.193	0.022	-0.039	-0.023	-0.003	-0.004	0.053	0.168	0.106	-0.269	1

Note a: Table 1A shows the descriptive analysis for the initial sample. The initial sample is used to examine the question of (1) whether the arrival of ChatGPT create more potential answers and (2) whether the arrival of ChatGPT brings about more accepted solutions.

Table 1B. Summary Statistics And Correlation: Sample for question with an accepted answer

	Mean	S.D.	Min	Max	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Time to Obtain Accepted Solution (ln) (1)	0.52	1.04	0	5.88	1														
Quantity of Questions(ln) (2)	0.85	0.28	0.69	2.48	-0.056	1													
Quantity of Answer(ln) (3)	0.18	0.4	0	4.39	0.086	0.144	1												
View (ln) (4)	5.16	1.27	2.4	10.78	0.279	-0.007	0.049	1											
Length(ln) (5)	5.33	0.86	2.3	9.75	0.004	0.103	0.036	0.054	1										
Code (ln) (6)	0.64	0.18	0	0.69	-0.056	0.05	0.017	-0.013	0.308	1									
Edit for Body (ln) (7)	0.41	0.58	0	5.79	-0.02	0.336	0.352	0.043	0.18	0.098	1								
Edit for Tag (ln) (8)	0.04	0.19	0	3.3	-0.007	0.119	0.182	0.041	0.021	0.024	0.29	1							
Edit for Title (ln) (9)	0.06	0.23	0	3.83	-0.008	0.168	0.204	0.032	0.038	0.025	0.37	0.285	1						
Reputation (ln) (10)	0.25	0.51	0	3.04	-0.025	0.111	0.119	0.015	0.019	0.022	0.12	0.042	0.055	1					
Scope(ln) (11)	1.36	0.3	0.69	1.79	0.059	0.006	0.045	0.178	0.181	0.036	0.062	0.085	0.044	0.02	1				
Complexity (ln)(12)	1.24	0.07	0	1.43	0.038	0	0.039	0.11	0.076	-0.014	0.02	0.029	0.02	0.006	0.537	1			
Chains to Obtain Solutions (ln) (13)	0.77	0.18	0	2.08	0.082	0.01	-0.009	0.069	0.016	0.042	0.022	-0.026	-0.011	0.003	-0.003	-0.016	1		
Search Depth (14)	2.53	1.41	1	17.21	-0.111	0.217	-0.055	-0.161	0.059	0.08	0.063	0.01	0.009	0.057	-0.089	-0.122	0.046	1	
Search Scope (15)	0.08	0.15	0	1	0.123	0.002	-0.009	0.199	-0.002	-0.042	-0.041	-0.006	-0.005	0.118	0.184	0.114	0.002	-0.328	1

Note a: Table 1A shows the descriptive analysis for the initial sample. The initial sample is used to examine the question of whether the arrival of ChatGpt has the impacts on the time to evaluate the accepted solution.

Table 2. Validity Test

	(1)
DEPENDENT VARIABLES	Proportion of Question with Answer
Treatment × Post	0.033***
	(0.004)
Quantity of Questions (ln)	-0.031***
	(0.001)
Quantity of Answer (ln)	0.140***
	(0.000)
View (ln)	0.096***
	(0.000)
Length (ln)	-0.024***
	(0.000)
Code (ln)	0.097***
	(0.000)
Edit for Body (ln)	0.001
	(0.904)
Edit for Tag (ln)	-0.058***
	(0.000)
Edit for Title (ln)	-0.011
	(0.398)
Reputation (ln)	0.006
	(0.257)
Scope (ln)	-0.031**
	(0.036)
Complexity (ln)	-0.379***
	(0.000)
Constant	0.845***
	(0.000)
Individual fixed effects	Y
Week fixed effects	Y
Observations	20,235
R-squared	0.303

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed

Note b: Model 1 employs OLS regression with individual and week fixed effects

Table 3. Main Test

	Model 1	Model 2
DEPENDENT VARIABLES	Proportion of Question with Accepted Solution	Time to Obtain Accepted Solution
Treatment × Post	0.012	0.087***
	(0.333)	(0.000)
Quantity of Questions (ln)	0.002	-0.078***
	(0.886)	(0.007)
Quantity of Answer (ln)	0.014	0.289***
	(0.183)	(0.000)
View (ln)	0.060***	0.061***
	(0.000)	(0.000)
Length(ln)	-0.016***	0.020*
	(0.000)	(0.089)
Code (ln)	0.112***	-0.183***
	(0.000)	(0.001)
Edit for Body (ln)	-0.005	-0.014
	(0.505)	(0.394)
Edit for Tag (ln)	-0.045**	-0.023
	(0.015)	(0.579)
Edit for Title (ln)	-0.015	-0.044
	(0.312)	(0.243)
Reputation (ln)	0.018***	-0.049***
	(0.002)	(0.001)
Scope (ln)	-0.024	0.102***
	(0.129)	(0.009)
Complexity (ln)	-0.390***	0.193
	(0.000)	(0.219)
Chains to Obtain Solutions		0.533***
		(0.000)
Constant	0.670***	-0.544***
	(0.000)	(0.006)
Individual fixed effects	Y	Y
Week fixed effects	Y	Y
Observations	20,235	17,953
R-squared	0.344	0.502

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed

Note b: Model 1 and Model 2 employ OLS regression with individual and week fixed effects

Table 4. Subsample Analysis: Search Depth

	Model 1A	Model 1B	Model 2A	Model 2B
DEPDENT VARIABLES	Proportion of Question with Accepted Solution		Time to Obtain Accepted Solution	
Treatment × Post	0.009	0.016	0.032	0.136***
	(0.635)	(0.404)	(0.334)	(0.000)
Quantity of Questions (ln)	0.011	-0.026	-0.091***	-0.013
	(0.451)	(0.189)	(0.009)	(0.807)
Quantity of Answer (ln)	-0.004	0.030*	0.289***	0.292***
	(0.822)	(0.057)	(0.000)	(0.000)
View (ln)	0.059***	0.061***	0.058***	0.059***
	(0.000)	(0.000)	(0.000)	(0.000)
Length (ln)	-0.010	-0.023***	0.039***	-0.000
	(0.130)	(0.000)	(0.006)	(0.998)
Code (ln)	0.098***	0.131***	-0.134	-0.176**
	(0.001)	(0.000)	(0.100)	(0.027)
Edit for Body (ln)	-0.004	-0.006	-0.019	-0.011
	(0.692)	(0.599)	(0.335)	(0.705)
Edit for Tag (ln)	-0.022	-0.070**	-0.016	-0.013
	(0.326)	(0.021)	(0.742)	(0.870)
Edit for Title (ln)	-0.005	-0.038	-0.054	-0.065
	(0.810)	(0.124)	(0.176)	(0.349)
Reputation (ln)	0.004	0.045***	-0.002	-0.137***
	(0.610)	(0.000)	(0.901)	(0.000)
Scope (ln)	-0.054**	-0.001	0.045	0.147**
	(0.016)	(0.970)	(0.364)	(0.017)
Complexity (ln)	-0.445***	-0.314***	-0.073	0.351
	(0.000)	(0.000)	(0.747)	(0.116)
Chains to Obtain Solutions			0.413***	0.683***
			(0.000)	(0.000)
Constant	0.777***	0.562***	-0.246	-0.748***
	(0.000)	(0.000)	(0.381)	(0.008)
Individual fixed effects	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y
Observations	10,048	10,046	8,806	8,858
R-squared	0.328	0.377	0.466	0.529

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed

Note b: All models in Table 4 employ OLS regression with individual and week fixed effects

Note c: Model 1A and 2A employ the subsample of individuals with relatively high search depth. Model 1B and 2B employ the subsample of individuals with relatively low search depth

Table 4. Subsample Analysis: Search Scope

	Model 1A	Model 1B	Model 2A	Model 2B
DEPDENT VARIABLES	Proportion of Question with Accepted Solution		Time to Obtain Accepted Solution	
Treatment × Post	0.034*	0.004	0.127***	-0.024
	(0.070)	(0.847)	(0.000)	(0.521)
Quantity of Questions (ln)	0.015	0.009	-0.114**	-0.038
	(0.394)	(0.602)	(0.028)	(0.319)
Quantity of Answer (ln)	0.027*	0.001	0.324***	0.297***
	(0.071)	(0.954)	(0.000)	(0.000)
View (ln)	0.054***	0.067***	0.071***	0.051***
	(0.000)	(0.000)	(0.000)	(0.000)
Length(ln)	-0.022***	-0.012*	0.015	0.029*
	(0.001)	(0.078)	(0.452)	(0.066)
Code (ln)	0.109***	0.114***	-0.213**	-0.085
	(0.000)	(0.000)	(0.015)	(0.343)
Edit for Body (ln)	-0.007	-0.006	0.008	-0.018
	(0.493)	(0.573)	(0.777)	(0.372)
Edit for Tag (ln)	-0.070***	-0.016	0.037	-0.086*
	(0.005)	(0.566)	(0.612)	(0.082)
Edit for Title (ln)	-0.023	-0.018	-0.058	-0.036
	(0.312)	(0.436)	(0.449)	(0.419)
Reputation (ln)	0.045***	-0.004	-0.141***	0.001
	(0.000)	(0.603)	(0.000)	(0.945)
Scope (ln)	0.025	-0.059**	0.079	0.090*
	(0.312)	(0.014)	(0.259)	(0.091)
Complexity (ln)	-0.302***	-0.462***	0.235	0.146
	(0.002)	(0.000)	(0.412)	(0.486)
Chains to Obtain Solutions			0.577***	0.405***
			(0.000)	(0.000)
Constant	0.516***	0.770***	-0.496	-0.535**
	(0.000)	(0.000)	(0.170)	(0.040)
Individual fixed effects	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y
Observations	9,743	9,561	8,138	7,952
R-squared	0.420	0.356	0.544	0.514

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed

Note b: All model in Table 5 employ OLS regression with individual and week fixed effects

Note c: Model 1A and 2A employ the subsample of individuals with relatively high search scope. Model 1B and 2B employ the subsample of individuals with relatively low search scope.

Table 6. Robustness Check for the Validity Test

	Model 1A	Model 1B	Model 1C	Model 1D
DEPENDENT VARIABLES	Proportion of Question with Answer			
Treatment × Post	0.021*	0.028***	0.034***	0.038***
	(0.060)	(0.002)	(0.005)	(0.000)
Quantity of Questions (ln)	-0.042***	-0.022***	-0.032***	-0.036***
	(0.000)	(0.000)	(0.003)	(0.000)
Quantity of Answer (ln)	0.141***	0.120***	0.139***	0.137***
	(0.000)	(0.000)	(0.000)	(0.000)
View (ln)	0.082***	0.071***	0.096***	0.094***
	(0.000)	(0.000)	(0.000)	(0.000)
Length(ln)	-0.029***	-0.028***	-0.023***	-0.026***
	(0.000)	(0.000)	(0.000)	(0.000)
Code (ln)	0.087***	0.077***	0.088***	0.104***
	(0.000)	(0.000)	(0.000)	(0.000)
Edit for Body (ln)	0.005	-0.006	0.000	0.002
	(0.420)	(0.128)	(0.999)	(0.756)
Edit for Tag (ln)	-0.032*	-0.030***	-0.062***	-0.050***
	(0.066)	(0.005)	(0.000)	(0.001)
Edit for Title (ln)	-0.017	-0.010	-0.012	-0.007
	(0.238)	(0.245)	(0.417)	(0.570)
Reputation (ln)	0.012**	0.007*	0.007	0.002
	(0.034)	(0.051)	(0.224)	(0.615)
Scope (ln)	-0.040***	-0.027***	-0.020	-0.034**
	(0.004)	(0.007)	(0.211)	(0.012)
Complexity (ln)	-0.406***	-0.409***	-0.388***	-0.363***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	1.004***	1.057***	0.843***	0.848***
	(0.000)	(0.000)	(0.000)	(0.000)
Individual fixed effects	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y
Observations	20,243	38,468	17,620	22,724
R-squared	0.306	0.295	0.324	0.286

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed

Note b: All models in Table 6 employ OLS regression with individual and week fixed effects.

Note c: Model 1A and 1B act as robustness checks for different matched samples to rule out biased estimation caused by the selection of the matched sample. Model 1A employs potential matched individuals who posted at least one question 10 weeks before and after November 30, 2020. Model 1B employs potential matched individuals who posted at least one question 10 weeks before and after November 30 in both 2020 and 2021 as the pseudo control group.

Note d: Model 1C and 1D act as robustness checks for different matched samples to rule out biased estimation caused by the window length selection. Model 1C includes 8 weeks before and after the arrival of ChatGPT as the window length. Model 1D includes 12 weeks before and after the arrival of ChatGPT as the window length.

Table 7. Robustness Check for the Main Test

	Model 1A	Model 1B	Model 1C	Model 1D	Model 2A	Model 2B	Model 2C	Model 2D
DEPENDENT VARIABLES	Proportion of Question with Accepted Solution				Time to Obtain Accepted Solution			
Treatment × Post	0.007	0.009	0.009	0.016	0.106***	0.085***	0.091**	0.082***
	(0.587)	(0.390)	(0.500)	(0.201)	(0.008)	(0.004)	(0.038)	(0.002)
Quantity of Questions (ln)	0.012	0.012	-0.002	0.001	-0.028	0.008	-0.096**	-0.070**
	(0.304)	(0.127)	(0.882)	(0.914)	(0.518)	(0.808)	(0.031)	(0.016)
Quantity of Answer (ln)	0.017	0.014*	0.016	0.012	0.260***	0.349***	0.386***	0.344***
	(0.116)	(0.060)	(0.172)	(0.255)	(0.000)	(0.000)	(0.000)	(0.000)
View (ln)	0.045***	0.046***	0.060***	0.060***	0.093***	0.056***	0.037**	0.054***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.014)	(0.000)
Length(ln)	-0.027***	-0.021***	-0.013***	-0.017***	0.038*	0.063***	0.014	0.024**
	(0.000)	(0.000)	(0.007)	(0.000)	(0.056)	(0.000)	(0.476)	(0.039)
Code (ln)	0.119***	0.103***	0.109***	0.110***	-0.147	-0.232***	-0.180*	-0.115**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.135)	(0.007)	(0.088)	(0.040)
Edit for Body (ln)	0.003	-0.005	-0.006	-0.001	-0.016	-0.013	-0.006	-0.033**
	(0.666)	(0.287)	(0.481)	(0.881)	(0.536)	(0.548)	(0.841)	(0.047)
Edit for Tag (ln)	-0.034*	-0.018	-0.047**	-0.045***	0.014	0.019	0.048	-0.025
	(0.088)	(0.159)	(0.021)	(0.007)	(0.826)	(0.718)	(0.445)	(0.584)
Edit for Title (ln)	-0.021	-0.012	-0.015	-0.012	0.051	-0.013	-0.045	-0.012
	(0.204)	(0.293)	(0.372)	(0.404)	(0.379)	(0.767)	(0.451)	(0.767)
Reputation (ln)	0.027***	0.018***	0.016**	0.018***	-0.031	-0.035**	-0.060***	-0.044***
	(0.000)	(0.000)	(0.016)	(0.001)	(0.157)	(0.042)	(0.007)	(0.003)
Scope(ln)	-0.032**	-0.036***	-0.013	-0.032**	0.015	0.038	0.173**	0.087**
	(0.042)	(0.003)	(0.458)	(0.031)	(0.820)	(0.519)	(0.018)	(0.020)
Complexity (ln)	-0.402***	-0.428***	-0.393***	-0.366***	0.868***	0.237	-0.150	0.066
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.285)	(0.587)	(0.671)
Chains to Obtain Solutions					0.542***	0.615***	0.408***	0.497***
					(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.810***	0.856***	0.652***	0.659***	-1.546***	-0.749***	0.009	-0.403**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)	(0.978)	(0.042)
Individual fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	20,243	38,468	17,620	22,724	7,155	10,783	4,933	16,202
R-squared	0.335	0.335	0.364	0.327	0.410	0.402	0.491	0.500

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed

Note b: All Model in Table 7 employ OLS regression with individual and week fixed effects.

Note c: Model 1A, 2A, 1B and 2B act as robustness checks for different matched samples to rule out biased estimation caused by the selection of the matched sample. Model 1A and 2A employs potential matched individuals who posted at least one question 10 weeks before and after November 30, 2020. Model 1B and 2B employs potential matched individuals who posted at least one question 10 weeks before and after November 30 in both 2020 and 2021 as the pseudo control group.

Note d: Model 1C, 2C, 1D and 2D act as robustness checks for different matched samples to rule out biased estimation caused by the window length selection. Model 1C and 2C includes 8 weeks before and after the arrival of ChatGPT as the window length. Model 1D and 2D includes 12 weeks before and after the arrival of ChatGPT as the window length.

Table 8A: Robustness Check for Additional Analysis: Search Depth

	Model 1A	Model 1B	Model 2A	Model 2B	Model 3A	Model 3B	Model4A	Model 4B
DEPENDENT VARIABLES	Proportion of Question with Accepted Solution							
Treatment × Post	-0.007	0.009	0.014	0.007	0.001	0.012	0.014	0.019
	(0.709)	(0.651)	(0.328)	(0.658)	(0.940)	(0.538)	(0.413)	(0.299)
Quantity of Questions(ln)	-0.005	0.039**	0.005	0.014	0.007	-0.027	0.011	-0.019
	(0.711)	(0.049)	(0.569)	(0.328)	(0.660)	(0.232)	(0.393)	(0.312)
Quantity of Answer(ln)	0.001	0.033**	0.018*	0.013	-0.000	0.028*	-0.003	0.022
	(0.962)	(0.030)	(0.081)	(0.240)	(0.996)	(0.099)	(0.810)	(0.133)
View (ln)	0.040***	0.048***	0.040***	0.051***	0.059***	0.059***	0.059***	0.061***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Length(ln)	-0.023***	-0.031***	-0.017***	-0.027***	-0.009	-0.021***	-0.009	-0.027***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.206)	(0.006)	(0.131)	(0.000)
Code (ln)	0.150***	0.093***	0.129***	0.090***	0.098***	0.124***	0.094***	0.131***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.001)	(0.000)
Edit for Body (ln)	0.012	-0.010	0.001	-0.010	-0.006	-0.003	-0.003	0.004
	(0.193)	(0.357)	(0.931)	(0.198)	(0.598)	(0.806)	(0.735)	(0.722)
Edit for Tag (ln)	-0.028	-0.045	-0.006	-0.035*	-0.012	-0.076**	-0.022	-0.076***
	(0.271)	(0.161)	(0.730)	(0.094)	(0.630)	(0.023)	(0.287)	(0.008)
Edit for Title (ln)	-0.027	-0.004	-0.010	-0.016	0.008	-0.053**	0.001	-0.038
	(0.220)	(0.866)	(0.469)	(0.365)	(0.714)	(0.042)	(0.965)	(0.105)
Reputation (ln)	0.026***	0.024**	0.008	0.031***	-0.005	0.056***	0.003	0.050***
	(0.001)	(0.017)	(0.117)	(0.000)	(0.536)	(0.000)	(0.693)	(0.000)
Scope(ln)	-0.043*	-0.018	-0.033*	-0.040**	-0.044*	0.013	-0.067***	0.002
	(0.055)	(0.422)	(0.055)	(0.022)	(0.067)	(0.600)	(0.001)	(0.927)
Complexity (ln)	-0.365***	-0.446***	-0.495***	-0.373***	-0.429***	-0.327***	-0.388***	-0.334***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Constant	0.799***	0.828***	0.943***	0.782***	0.741***	0.557***	0.716***	0.595***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	10,051	10,056	19,121	19,133	8,738	8,727	11,726	10,850
R-squared	0.307	0.371	0.325	0.359	0.348	0.397	0.313	0.363

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed

Note b: All models in Table 8 employ OLS regression with individual and week fixed effects.

Note c: Model 1A, 1B, 2A and 2B act as robustness checks for different matched samples to rule out biased estimation caused by the selection of the matched sample. Model 1A and 1B employ potential matched individuals who posted at least one question 10 weeks before and after November 30, 2020. Model 2A and 2B employs potential matched individuals who posted at least one question 10 weeks before and after November 30 in both 2020 and 2021 as the pseudo control group.

Note d: Model 3A, 3B, 4A and 4B act as robustness checks for different matched samples to rule out biased estimation caused by the window length selection. Model 3A and 3B includes 8 weeks before and after the arrival of ChatGPT as the window length. Model 4A and 4B includes 12 weeks before and after the arrival of ChatGPT as the window length.

Note e: Model 1A, 2A, 3A and 4A employ the subsample of individuals with relatively high search depth. Model 1B, 2B, 3B and 4B employ the subsample of individuals with relatively low search depth.

Table 8B: Robustness Check for Additional Analysis: Search Depth

	Model 1A	Model 1B	Model 2A	Model 2B	Model 3A	Model 3B	Model4A	Model 4B
DEPENDENT VARIABLES	Time to Obtain Accepted Solution							
Treatment × Post	0.030	0.164***	0.026	0.138***	-0.044	0.194***	-0.058	0.138***
	(0.564)	(0.008)	(0.513)	(0.002)	(0.428)	(0.003)	(0.168)	(0.000)
Quantity of Questions(ln)	-0.012	-0.025	0.009	0.005	-0.112**	-0.027	-0.060	-0.051
	(0.809)	(0.751)	(0.826)	(0.933)	(0.022)	(0.779)	(0.115)	(0.277)
Quantity of Answer(ln)	0.252***	0.288***	0.319***	0.396***	0.324***	0.442***	0.253***	0.398***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
View (ln)	0.072***	0.110***	0.055***	0.054***	0.058***	0.019	0.044***	0.056***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.006)	(0.386)	(0.002)	(0.000)
Length(ln)	0.061**	0.023	0.090***	0.037	-0.008	0.034	0.036**	0.020
	(0.029)	(0.428)	(0.000)	(0.106)	(0.741)	(0.270)	(0.026)	(0.205)
Code (ln)	-0.105	-0.127	-0.089	-0.259**	-0.131	-0.213	-0.068	-0.116*
	(0.462)	(0.333)	(0.537)	(0.023)	(0.289)	(0.160)	(0.490)	(0.088)
Edit for Body (ln)	-0.045	0.032	0.009	-0.023	0.007	-0.009	-0.025	-0.029
	(0.203)	(0.424)	(0.764)	(0.502)	(0.844)	(0.848)	(0.255)	(0.220)
Edit for Tag (ln)	0.002	0.078	-0.004	0.010	0.023	0.084	-0.093*	0.039
	(0.977)	(0.445)	(0.956)	(0.909)	(0.725)	(0.520)	(0.098)	(0.572)
Edit for Title (ln)	0.084	0.040	0.017	-0.042	-0.103	0.024	-0.016	-0.016
	(0.310)	(0.652)	(0.756)	(0.538)	(0.142)	(0.821)	(0.712)	(0.811)
Reputation (ln)	-0.006	-0.084**	-0.013	-0.062**	-0.033	-0.111***	0.021	-0.116***
	(0.831)	(0.023)	(0.545)	(0.050)	(0.187)	(0.009)	(0.296)	(0.000)
Scope(ln)	0.042	0.009	0.006	0.063	0.163**	0.175	0.047	0.104**
	(0.636)	(0.931)	(0.938)	(0.477)	(0.028)	(0.156)	(0.406)	(0.041)
Complexity (ln)	0.703*	1.074***	0.433	0.166	0.115	-0.453	-0.040	0.120
	(0.061)	(0.003)	(0.155)	(0.606)	(0.698)	(0.314)	(0.869)	(0.555)
Chains to Obtain Solutions	0.442***	0.640***	0.499***	0.716***	0.223**	0.642***	0.451***	0.520***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)	(0.000)
Constant	-1.416***	-1.843***	-1.187***	-0.509	-0.262	0.272	-0.298	-0.471*
	(0.002)	(0.000)	(0.002)	(0.191)	(0.507)	(0.613)	(0.326)	(0.068)
Individual fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,544	3,547	5,340	5,339	2,441	2,441	6,009	10,031
R-squared	0.419	0.421	0.371	0.432	0.439	0.524	0.442	0.528

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed

Note b: All models in Table 9 employ OLS regression with individual and week fixed effects.

Note c: Model 1A, 1B, 2A and 2B act as robustness checks for different matched samples to rule out biased estimation caused by the selection of the matched sample. Model 1A and 1B employ potential matched individuals who posted at least one question 10 weeks before and after November 30, 2020. Model 2A and 2B employs potential matched individuals who posted at least one question 10 weeks before and after November 30 in both 2020 and 2021 as the pseudo control group.

Note d: Model 3A, 3B, 4A and 4B act as robustness checks for different matched samples to rule out biased estimation caused by the window length selection. Model 3A and 3B includes 8 weeks before and after the arrival of ChatGPT as the window length. Model 4A and 4B includes 12 weeks before and after the arrival of ChatGPT as the window length.

Note e: Model 1A, 2A, 3A and 4A employ the subsample of individuals with relatively high search depth. Model 1B, 2B, 3B and 4B employ the subsample of individuals with relatively low search depth.

Table 9A: Robustness Check for Additional Analysis: Search Scope

	Model 1A	Model 1B	Model 2A	Model 2B	Model 3A	Model 3B	Model4A	Model 4B
DEPENDENT VARIABLES	Proportion of Question with Accepted Solution							
Treatment × Post	0.045**	-0.013	0.026†	0.005	0.033*	-0.006	0.026†	0.004
	(0.020)	(0.512)	(0.110)	(0.758)	(0.094)	(0.788)	(0.144)	(0.828)
Quantity of Questions (ln)	0.005	0.023	0.019	0.017	0.011	-0.001	0.007	0.007
	(0.793)	(0.195)	(0.112)	(0.147)	(0.584)	(0.969)	(0.693)	(0.656)
Quantity of Answer (ln)	0.026*	-0.006	0.013	0.015	0.017	0.012	0.019	-0.001
	(0.086)	(0.743)	(0.230)	(0.205)	(0.314)	(0.527)	(0.198)	(0.959)
View (ln)	0.042***	0.049***	0.047***	0.048***	0.052***	0.065***	0.054***	0.065***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Length(ln)	-0.022***	-0.030***	-0.020***	-0.024***	-0.021***	-0.009	-0.024***	-0.013**
	(0.001)	(0.000)	(0.000)	(0.000)	(0.005)	(0.221)	(0.000)	(0.035)
Code (ln)	0.135***	0.081**	0.076***	0.128***	0.106***	0.110***	0.111***	0.113***
	(0.000)	(0.011)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Edit for Body (ln)	-0.008	0.015	-0.016**	-0.000	-0.011	-0.008	-0.004	-0.003
	(0.434)	(0.175)	(0.042)	(0.956)	(0.349)	(0.522)	(0.687)	(0.719)
Edit for Tag (ln)	-0.023	-0.028	-0.030	-0.011	-0.075***	0.000	-0.063***	-0.026
	(0.414)	(0.351)	(0.104)	(0.612)	(0.008)	(0.994)	(0.009)	(0.298)
Edit for Title (ln)	-0.021	-0.031	-0.012	0.001	-0.031	-0.010	-0.024	-0.002
	(0.396)	(0.206)	(0.447)	(0.964)	(0.186)	(0.707)	(0.242)	(0.940)
Reputation (ln)	0.034***	0.015*	0.044***	-0.001	0.047***	-0.009	0.050***	-0.004
	(0.002)	(0.060)	(0.000)	(0.883)	(0.000)	(0.295)	(0.000)	(0.574)
Scope(ln)	-0.012	-0.027	-0.018	-0.033*	0.035	-0.040	0.013	-0.064***
	(0.649)	(0.272)	(0.366)	(0.063)	(0.206)	(0.122)	(0.599)	(0.003)
Complexity of (ln)	-0.547***	-0.315***	-0.433***	-0.427***	-0.274**	-0.479***	-0.342***	-0.406***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)	(0.000)
Constant	0.940***	0.721***	0.822***	0.846***	0.481***	0.768***	0.603***	0.720***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Individual fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	9,746	9,544	18,517	18,254	8,419	8,217	10,668	11,197
R-squared	0.413	0.352	0.406	0.363	0.441	0.374	0.404	0.338

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1, † indicates p<0.15. All tests are two-tailed

Note b: All models in Table 10 employ OLS regression with individual and week fixed effects.

Note c: Model 1A, 1B, 2A and 2B act as robustness checks for different matched samples to rule out biased estimation caused by the selection of the matched sample. Model 1A and 1B employ potential matched individuals who posted at least one question 10 weeks before and after November 30, 2020. Model 2A and 2B employs potential matched individuals who posted at least one question 10 weeks before and after November 30 in both 2020 and 2021 as the pseudo control group.

Note d: Model 3A, 3B, 4A and 4B act as robustness checks for different matched samples to rule out biased estimation caused by the window length selection. Model 3A and 3B includes 8 weeks before and after the arrival of ChatGPT as the window length. Model 4A and 4B includes 12 weeks before and after the arrival of ChatGPT as the window length.

Note e: Model 1A, 2A, 3A and 4A employ the subsample of individuals with relatively high search scope. Model 1B, 2B, 3B and 4B employ the subsample of individuals with relatively low search scope.

Table 9B: Robustness Check for Additional Analysis: Search Scope

	Model 1A	Model 1B	Model 2A	Model 2B	Model 3A	Model 3B	Model4A	Model 4B
DEPENDENT VARIABLES	Proportion of Question with Accepted Solution							
Treatment × Post	0.108*	0.063	0.133***	-0.002	0.150**	-0.021	0.130***	-0.043
	(0.085)	(0.292)	(0.004)	(0.954)	(0.026)	(0.737)	(0.000)	(0.327)
Quantity of Questions (ln)	0.023	-0.044	0.013	0.038	-0.079	-0.063	-0.089*	-0.070
	(0.744)	(0.458)	(0.818)	(0.440)	(0.379)	(0.237)	(0.053)	(0.122)
Quantity of Answer (ln)	0.264***	0.278***	0.314***	0.396***	0.484***	0.302***	0.368***	0.299***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
View (ln)	0.097***	0.068***	0.061***	0.054***	0.053**	0.018	0.049***	0.058***
	(0.000)	(0.002)	(0.000)	(0.001)	(0.023)	(0.420)	(0.000)	(0.000)
Length(ln)	-0.017	0.085***	0.059**	0.068***	0.017	0.016	0.029	0.017
	(0.576)	(0.004)	(0.014)	(0.002)	(0.610)	(0.561)	(0.105)	(0.290)
Code (ln)	-0.054	-0.192	-0.322***	-0.258*	-0.212	-0.093	-0.161**	-0.056
	(0.696)	(0.236)	(0.007)	(0.066)	(0.199)	(0.533)	(0.035)	(0.608)
Edit for Body (ln)	0.011	-0.030	0.002	-0.021	-0.019	-0.026	-0.014	-0.035
	(0.803)	(0.413)	(0.964)	(0.499)	(0.688)	(0.456)	(0.581)	(0.120)
Edit for Tag (ln)	0.096	-0.015	-0.006	0.064	0.038	0.042	-0.015	-0.092
	(0.406)	(0.840)	(0.939)	(0.385)	(0.758)	(0.568)	(0.813)	(0.184)
Edit for Title (ln)	-0.004	0.049	-0.040	0.039	0.012	-0.072	-0.019	0.002
	(0.961)	(0.564)	(0.575)	(0.496)	(0.905)	(0.318)	(0.758)	(0.972)
Reputation (ln)	-0.129***	0.026	-0.051	-0.012	-0.073*	-0.066**	-0.114***	0.005
	(0.002)	(0.337)	(0.111)	(0.588)	(0.098)	(0.015)	(0.000)	(0.828)
Scope(ln)	0.078	0.026	0.138	-0.010	0.014	0.301***	0.066	0.080
	(0.533)	(0.771)	(0.184)	(0.903)	(0.924)	(0.001)	(0.290)	(0.128)
Complexity of Question (ln)	1.078**	0.470	0.302	-0.036	-0.128	-0.261	0.147	-0.101
	(0.028)	(0.156)	(0.417)	(0.907)	(0.786)	(0.503)	(0.553)	(0.638)
Constant	0.831***	0.396***	0.631***	0.612***	0.354**	0.396***	0.533***	0.441***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.016)	(0.000)	(0.000)	(0.000)
Chains to Obtain Solutions	-1.884***	-1.109***	-0.880*	-0.445	0.228	-0.054	-0.396	-0.228
	(0.002)	(0.007)	(0.051)	(0.226)	(0.698)	(0.907)	(0.204)	(0.408)
Individual fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Week fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	3,400	3,345	5,108	5,066	2,309	2,270	8,352	6,239
R-squared	0.454	0.455	0.460	0.423	0.518	0.546	0.552	0.492

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed

Note b: All Models in Table 11 employ OLS regression with individual and week fixed effects.

Note c: Model 1A, 1B, 2A and 2B act as robustness checks for different matched samples to rule out biased estimation caused by the selection of the matched sample. Model 1A and 1B employ potential matched individuals who posted at least one question 10 weeks before and after November 30, 2020. Model 2A and 2B employs potential matched individuals who posted at least one question 10 weeks before and after November 30 in both 2020 and 2021 as the pseudo control group.

Note d: Model 3A, 3B, 4A and 4B act as robustness checks for different matched samples to rule out biased estimation caused by the window length selection. Model 3A and 3B includes 8 weeks before and after the arrival of ChatGPT as the window length. Model 4A and 4B includes 12 weeks before and after the arrival of ChatGPT as the window length.

Note e: Model 1A, 2A, 3A and 4A employ the subsample of individuals with relatively high search scope. Model 1B, 2B, 3B and 4B employ the subsample of individuals with relatively low search scope.

Table 10. Robustness Check for Endogenous Trend

	Model 1	Model 2	Model3
DEPENDENT VARIABLES	Proportion of Question with Answer	Time to Obtain Accepted Solution	Time to Obtain Accepted Solution
Treatment × Post	0.005	0.006	0.047
	(0.510)	(0.470)	(0.269)
Quantity of Questions (ln)	-0.027***	0.006	-0.036
	(0.000)	(0.429)	(0.343)
Quantity of Answer (ln)	0.096***	0.010	0.471***
	(0.000)	(0.172)	(0.000)
View (ln)	0.059***	0.040***	0.081***
	(0.000)	(0.000)	(0.000)
Length(ln)	-0.019***	-0.014***	0.059***
	(0.000)	(0.000)	(0.000)
Code (ln)	0.049***	0.080***	-0.328***
	(0.000)	(0.000)	(0.000)
Edit for Body (ln)	-0.014***	-0.011**	-0.066***
	(0.000)	(0.015)	(0.004)
Edit for Tag (ln)	-0.023**	-0.036***	-0.012
	(0.014)	(0.003)	(0.836)
Edit for Title (ln)	-0.013	-0.010	0.005
	(0.111)	(0.347)	(0.921)
Reputation (ln)	0.003	0.033***	-0.059***
	(0.373)	(0.000)	(0.002)
Scope(ln)	-0.029***	-0.038***	0.142**
	(0.001)	(0.001)	(0.012)
Complexity (ln)	-0.306***	-0.375***	-0.061
	(0.000)	(0.000)	(0.789)
Chains to Obtain Solutions			0.811***
Constant	0.995***	0.828***	-0.502*
	(0.000)	(0.000)	(0.068)
Individual fixed effects	Y	Y	Y
Week fixed effects	Y	Y	Y
Observations	41,482	41,482	13,059
R-squared	0.253	0.335	0.343

Note a: P-value is included in parentheses. *** indicates p<0.01; ** indicates p<0.05; * indicates p<0.1. All tests are two-tailed
Note b: Model 1 and Model 2 employ OLS regression with individual and week fixed effects

4.12 Figures

Figure 1A. Parelle Trend Test for Dependent Variable of Proportion of Questions with Answers

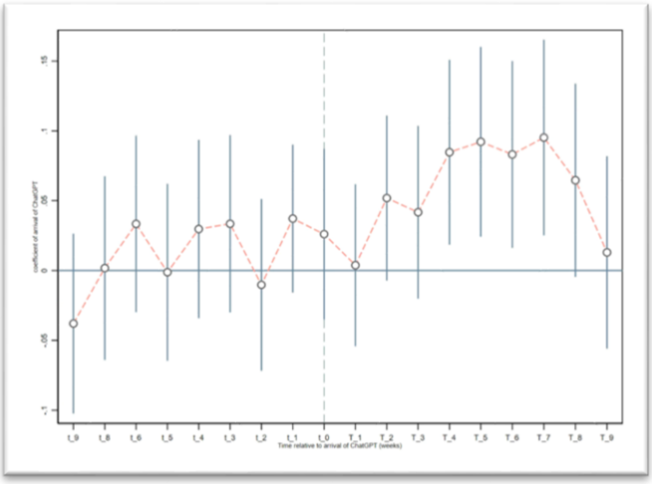

Figure 1B. Parelle Trend Test for Dependent Variable of Proportion of Questions with Accepted Solution

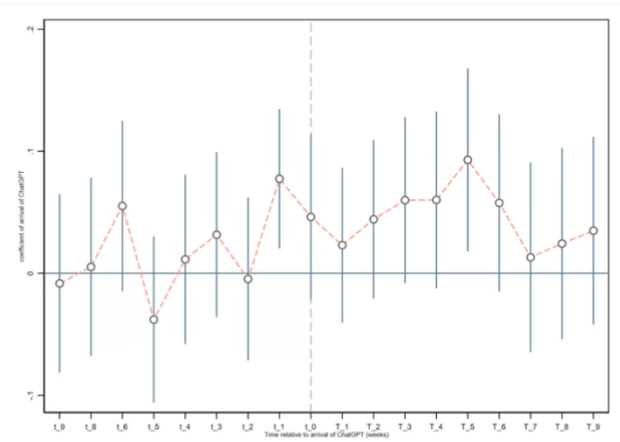

Figure 1C. Parelle Trend Test for Dependent Variable of Time to Obtain Accepted Solutions