Integrating Generative Artificial Intelligence and Humans in Management under Uncertainty

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Abstract

This study investigates the effects of performance uncertainty of Generative Artificial Intelligence (Gen-AI) and market uncertainty on strategic decision-making in AI-human collaboration using a real options framework. By modelling four strategies—sole human labour, exclusive AI use, task distribution between humans and AI, and the "Human in the Loop" approach—this research demonstrates that higher probabilities of AI success lead to earlier adoption of AI-inclusive strategies. Conversely, greater market uncertainty postpones strategy transitions but increases the importance of human intervention. The findings suggest that exclusive reliance on AI is suboptimal, with the "Human in the Loop" strategy proving to be the most advantageous. This research offers a dynamic model for AI adoption and provides managerial insights into optimizing AI-human collaboration under uncertainty.

Keywords: Generative AI, Task allocation, Human in the loop, Uncertainty, Real options.
JEL codes: C60, J21, J22

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1. Introduction

There has been a significant increase in the capabilities and applications of generative artificial intelligence (Gen-AI) in various fields in recent years, particularly since the launch of Chatgpt (Heidt, 2023; Sandrini and Somogyi, 2023). Gen-AI is a revolutionary tool that changes the way human labour works and cooperates with AI, especially in labour-intensive workplaces (Eloundou et al., 2023; Walkowiak, 2023). Currently, Gen-AI has been widely used in the areas of Customer operations, marketing and sales, software engineering, and R&D.

Generative AI, particularly large language models, has recently attracted considerable attention from managers, urging executives and boards to integrate these technologies into their digital strategies (Li et al., 2021; Paschen et al., 2020). According to a recent McKinsey report, the most significant business development in 2023—and arguably the past decade—has been the emergence of generative AI, which has swiftly become a top priority for CEOs at numerous companies (Hatami and Segel, 2023). Furthermore, the incorporation of AI opens up both new opportunities and challenges for research in organizational strategic management (Haefner et al., 2021; Von Krogh, 2018).

However, existing research has yet to clearly define the optimal modes of AI adoption. Previous studies often overlook the uncertain nature of Gen-AI and the dynamic of market competition. Gen-AI, with its ability to produce novel and imaginative outputs, offers a revolutionary approach to outsourcing creative tasks; nevertheless, its reliability and performance are still uncertain. Market demand uncertainty for specific tasks also influences the adoption of Gen-AI. Moreover, Unlike traditional technologies that serve as mere tools, AI involves a high level of social interaction. Managers must navigate the dual challenges of effectively managing "AI employees" and promoting collaboration between human workers and AI. Therefore, this paper aims to investigate how market and technological uncertainties impact organizational decision-making in terms of Gen-AI adoptions and human-AI collaboration.

Recent scholars have paid attention to investigating the adoption of Artificial intelligence in management (e.g., Krakowski et al., 2023; Gaessler and Piezunka, 2023; Tong et al., 2021), especially the interaction between human and artificial intelligence due to the explosive rise of AI technology. Van den Broek et al. (2021) and Sakka et al. (2022) examines the employee selection between experts and AI. Choudhury et al. (2020) and Balasubramanian et al. (2022) study the substitution between human and AI. Gnewuch et al. (2023) and Raisch and Fomina (2023) explore the collaboration (combination) between humans and AI. These studies lay the foundation for investigating the AI-human collaboration paradigm, yet a comprehensive analysis of when and how to implement it is lacking.

In addition, many technology adoption models fail to account for uncertainty, particularly regarding technology uncertainty (Ameye et al., 2023). Such models often assume that firms have a clear understanding of a technology's performance (e.g., Mishra et al., 2022), which may not hold, especially in the case of Generative Artificial Intelligence (Gen-AI). Gen-AI, characterized by its complexity and rapid development, introduces significant uncertainty regarding its technical performance and potential applications. For instance, the evolution of large language models like OpenAI's ChatGPT4 demonstrates the rapid advancements in AI technology and its potential to challenge established digital technologies. Aside from technological uncertainty, market demand uncertainty also plays a crucial role in firms' AI adoption decisions, shaping their expectations of future profit flows (Nelson, 1961; Gans, 2023; O'Connor and Wilson, 2021). As firms make decisions regarding AI adoption, these choices, in turn, influence their profit flow and overall performance.

In technology adoption decisions, firms encounter a myriad of strategic choices, each entailing distinct real options (Dixit and Pindyck, 1994). Firstly, firms possess the "option to adopt" a given technology, intricately linked to the anticipated returns associated with its adoption. Concurrently, firms face the dynamic possibility of switching between strategies or abandoning their current strategy, adding layers of complexity to their decision-making. Secondly, there exists the "option to wait" instead of immediately adopting the technology, stemming from various sources such as evolving technology costs, improving performance over time, or learning opportunities (Trigeorgis and Reuer, 2017). Consequently, the determinants of technology adoption, especially uncertainties, influence the option value of adopting, switching, and abandoning (Wong, 2007; Luo and Yang, 2017; Arve and Zwart, 2023).

In this paper, I model the Gen-AI adoption in a real option setting and show the optimal collaboration strategies between Gen-AI and human labour under uncertainty by considering the option to adopt, switch and abandon. Specifically, I focus on four strategies based on the involvement of Gen-AI:

sole human participation, exclusive AI involvement, the distribution of tasks between humans and AI, and the "Human in the Loop" approach aimed at enhancing AI performance by humans by considering different levels of Gen-AI performance. I focus on exploring the impact of two key factors, namely the probability of achieving high-performance outcomes with Generative Artificial Intelligence (Gen-AI), which indicates the technology performance uncertainty, and market volatility, which implies the market uncertainty, on firms' strategic decision-making processes. Specifically, I investigate how these factors influence firms' thresholds for strategy adoption and exit, as well as the effectiveness of human intervention and task allocation to Gen-AI.

The model generates the following results. Firstly, as the probability of Gen-AI success increases, firms exhibit a tendency to adopt Gen-AI-inclusive strategies earlier. This suggests a growing confidence in the capabilities of Gen-AI and its potential to enhance performance outcomes. Secondly, higher market volatility introduces complexities into firms' strategic decisions. While it delays the timing of strategy transitions, it also amplifies the value of human intervention in mitigating uncertainty. This highlights the importance of adaptive strategies that leverage both Gen-AI and human expertise synergistically. Lastly, as Gen-AI performance becomes better, firms allocate a greater proportion of tasks to Gen-AI, but market volatility prompts a shift towards increased reliance on human intervention. This underscores the need for strategic planning that integrates both AI and human capabilities effectively.

In this paper, I make several significant contributions to the literature on Gen-AI adoption and strategic decision-making under market uncertainty. Firstly, I develop a dynamic model to analyze the adoption of Generative Artificial Intelligence (Gen-AI) within the context of market volatility. This model allows us to examine the optimal collaboration strategies between Gen-AI and human labor over time, providing insights into how firms can adapt their strategies in response to changing market conditions.

Secondly, I identify and analyze four distinct collaboration strategies based on the involvement of Gen-AI: exclusive AI participation, sole human involvement, task distribution between humans and AI, and the "Human in the Loop" approach aimed at enhancing AI performance with human intervention. By considering diverse costs incurred by humans and AI, varying levels of Gen-AI performance, and the augmented performance achieved through the "Human in the Loop" strategy, I offer a comprehensive analysis of the strategic options available to firms.

Lastly, I highlight the importance of human intervention in augmenting AI capabilities and improving decision-making processes. Our findings show the significance of collaborative approaches that leverage the complementary strengths of both AI and human labor, emphasizing the need for strategic planning that integrates these resources effectively to drive innovation and navigate uncertainties in dynamic business environments.

2. Model

To model the market uncertainty, I assume the market demand x_t follows a geometric Brownian motion:

$$dx_t = \mu x_t dt + \sigma x_t dW_t.$$

In the real options framework, human experts generate instantaneous profit, which is denoted by $\pi_h x_t$, while Gen-AI generates profit $\pi_g x_t$.

Concerning the involvement of Gen-AI and interaction between humans and Gen-AI, I consider managers to have four different strategies and the value of different strategies is denoted by V_i, where $\{i = 1, 2, 3, 4\}$.

1. *Human involvement only:* In traditional strategy, humans take all work without the involvement of Gen-AI. The performance of humans is certain and predictable. Therefore, the incremental profit for this strategy is π_h.

2. *AI involvement only:* Due to the rapid development of AI technology, AI employers can complete tasks automatically. However, the quality of the resulting performance is uncertain. To model this technology uncertainty of Gen-AI, I assume the quality of content generated by Gen-AI is uncertain (response uncertainty). To simplify the model, I assume there are two states. With probability p, the profit generated by Gen-AI is accurate and satisfying, which is the high state π_g^H. With probability $1 - p$, the profit generated by Gen-AI is not satisfying because of the fake or inaccurate information generated by Gen-AI, which is the low state π_g^L. Therefore, the incremental profit for this strategy is $p\pi_g^H + (1 - p)\pi_g^L$.

3. *Task distributed between AI and humans:* Due to the shortage of human labour or to improve efficiency and cost, it is common to distribute tasks between AI and humans. I assume the proportion of tasks allocated to Gen-AI is α. The incremental profit for this strategy is $\alpha[p\pi_g^H + (1-p)\pi_g^L] + (1 - \alpha)\pi_h$.

4. *Human in the loop:* In addition to task allocation between humans and Gen-AI, there is the concept of "human in the loop," where humans

engage with Gen-AI to enhance their proficiency in processing raw materials and reduce the uncertainty of Gen-AI performance. In this case, Gen-AI remains responsible for completing all tasks and the costs will be higher than strategy 3, but its performance can be augmented through human interaction. Humans are required to adjust the performance based on a minimal sample, leading to substantial labour savings. I assume the degree to increase the overall performance from strategy 2 is $\theta > 0$. Thus, the incremental profit for this strategy is $(1+\theta)(p\pi_g^H + (1-p)\pi_g^L)$.

I assume the cost of human labour only (strategy 1) is $c + \tilde{c}$, where c is the fixed cost. The degree of Gen-AI adoption would decrease this cost, so the cost of strategy 3 is $I(\alpha) = c + \tilde{c}(1-\alpha)^{\phi}$, where $\phi > 1$. When $\alpha = 1$, which is strategy 2, $I(0) = c$. When $\alpha = 0$, which is strategy 1, $I(0) = c + \tilde{c}$. For Strategy 4, there is an additional cost related to the improved efficiency $\theta \geq 0$. Based on Alvarez and Stenbacka (2007), this cost is strictly increasing and convex of the parameter, which can be expressed as $\tilde{I}(\theta) = \frac{\theta^k}{k}$, where scale parameter $k > 1$.

Therefore, the cost for strategy 1 is $I(0)$, cost for strategy 2 is $I(1)$, cost for strategy 3 is $I(\alpha)$ and cost for strategy 4 is $I(1) + \tilde{I}(\theta)$.

Proposition 1. *By taking the option to wait and the option to exercise into account, the payoffs of taking different strategies can be expressed as*

$$V_1(x) = E_x \int_0^{\infty} (e^{-rs}\pi_h x_s) ds - I(0) = \frac{\pi_h x}{r-\mu} - I(0), \tag{1}$$

$$V_2(x) = E_x \int_0^{\infty} [e^{-rs}(p\pi_g^H + (1-p)\pi_g^L) x_s] ds - I(1) = \frac{(p\pi_g^H + (1-p)\pi_g^L)x}{r-\mu} - I(1), \tag{2}$$

$$\begin{aligned} V_3(x) =& E_x \int_0^{\infty} \left[e^{-rs}[\alpha[p\pi_g^H + (1-p)\pi_g^L] + (1-\alpha)\pi_h] x_s\right] ds - I(\alpha) \\ =& \frac{[\alpha(p\pi_g^H + (1-p)\pi_g^L) + (1-\alpha)\pi_h]x}{r-\mu} - I(\alpha), \end{aligned} \tag{3}$$

$$\begin{aligned} V_4(x) =& E_x \int_0^{\infty} \left[(1+\theta)(p\pi_g^H + (1-p)\pi_g^L)\right] ds - I(1) - \tilde{I}(\theta) \\ =& (1+\theta)\frac{[p\pi_g^H + (1-p)\pi_g^L]x}{r-\mu} - I(1) - \tilde{I}(\theta). \end{aligned} \tag{4}$$

According to Dixit (1993), the optimal strategy is the one with the highest value at the action threshold.

I can solve the α^* from the first-order condition of the profit of adopting strategy 3 as follows:

$$V_3(\alpha) = V_3(x,\alpha) - I(\alpha) = \alpha\frac{(p\pi_g^H + (1-p)\pi_g^L - \pi_h)x}{r-\mu} + \frac{\pi_h x}{r-\mu} - c - \tilde{c}(1-\alpha)^{\phi},$$
$$\frac{\partial V_3}{\partial\alpha} = \frac{(p\pi_g^H + (1-p)\pi_g^L - \pi_h)x}{r-\mu} + \tilde{c}\phi(1-\alpha)^{\phi-1}, \quad \frac{\partial V_3^2}{\partial^2\alpha} = -\tilde{c}\phi(\phi-1)(1-\alpha)^{\phi-2} < 0,$$
$$\Rightarrow \alpha^*(x) = 1 - (\frac{(\pi_h - p\pi_g^H - (1-p)\pi_g^L)x}{(r-\mu)\tilde{c}\phi})^{\frac{1}{\phi-1}}.$$

Lemma 1. *When tasks are distributed between humans and Gen-AI, the optimal proportion allocated to Gen-AI can be expressed as*

$$\alpha^*(x) = 1 - (\frac{(\pi_h - p\pi_g^H - (1-p)\pi_g^L)x}{(r-\mu)\tilde{c}\phi})^{\frac{1}{\phi-1}} \in [0,1]. \tag{5}$$

- *If $\alpha^*(x)$ calculated from Equation (5) is negative, then $\alpha^* = 0$.*
- *If $\alpha^*(x)$ calculated from Equation (5) is greater than 1, then $\alpha^* = 1$.*

I can also solve the θ^* from the first-order condition of the profit of adopting strategy 4 as follows:

$$V_4(\theta) = V_4(x,\theta) - I(1) - \tilde{I}(\theta) = (1+\theta)\frac{(p\pi_g^H + (1-p)\pi_g^L)x}{r-\mu} - c - \frac{\theta^k}{k},$$
$$\frac{\partial V_4}{\partial\alpha} = \frac{(p\pi_g^H + (1-p)\pi_g^L)x}{r-\mu} - \theta^{k-1} = 0, \quad \frac{\partial V_4^2}{\partial^2\alpha} = -(k-1)\theta^{k-2} < 0,$$
$$\Rightarrow \theta^*(x) = (\frac{(p\pi_g^H + (1-p)\pi_g^L)x}{r-\mu})^{\frac{1}{k-1}}.$$

Lemma 2. *The optimal improved efficiency can be expressed as*

$$\theta^*(x) = (\frac{(p\pi_g^H + (1-p)\pi_g^L)x}{r-\mu})^{\frac{1}{k-1}} > 0. \tag{6}$$

- *If $\theta^*(x)$ calculated from Equation (6) is negative, then $\theta^* = 0$.*

2.1. Baseline model

Before the firm takes any strategy, the value is $A_i x^{\beta_1}$, where $i = \{1, 2, 3, 4\}$ and $\beta_1 = \frac{1}{2} - \frac{\mu}{\sigma^2} + \sqrt{(\frac{1}{2} - \frac{\mu}{\sigma^2})^2 + \frac{2r}{\sigma^2}} > 1$.

Corollary 1. *By applying the value-matching and smooth-pasting conditions, the action thresholds for options 1, 2, 3 and 4 from no action can be expressed as*

$$x_1 = \frac{\beta_1 (c + \tilde{c})(r - \mu)}{(\beta_1 - 1)\pi_h}, \tag{7}$$

$$x_2 = \frac{\beta_1 c (r - \mu)}{(\beta_1 - 1)(p\pi_g^H + (1-p)\pi_g^L)}, \tag{8}$$

$$x_3 = \frac{\beta_1}{\beta_1 - 1} \frac{(c + \tilde{c}(1-\alpha)^{\phi})(r - \mu)}{\alpha(p\pi_g^H + (1-p)\pi_g^L - \pi_h) + \pi_h}, \tag{9}$$

$$x_4 = \frac{\beta_1}{\beta_1 - 1} \frac{(c + \frac{\theta^k}{k})(r - \mu)}{(1+\theta)(p\pi_g^H + (1-p)\pi_g^L)}. \tag{10}$$

The corresponding arbitrary constant A_i for the firm's value before taking any action can be expressed as

$$A_1 = [\frac{\pi_h x_1}{r - mu} - c - \tilde{c}] x_1^{-\beta_1}, \tag{11}$$

$$A_2 = [\frac{(p\pi_g^H + (1-p)\pi_g^L) x_2}{r - mu} - c] x_2^{-\beta_1}, \tag{12}$$

$$A_3 = [\frac{\alpha(p\pi_g^H + (1-p)\pi_g^L - \pi_h) x_3}{r - mu} + \frac{\pi_h x_3}{r - mu} - c - \tilde{c}(1-\alpha)^{\phi}] x_3^{-\beta_1}, \tag{13}$$

$$A_4 = [\frac{(1+\theta)(p\pi_g^H + (1-p)\pi_g^L) x_4}{r - mu} - c - \frac{\theta^k}{k}] x_4^{-\beta_1}. \tag{14}$$

Specifically, $\alpha^*(x_3)$ and $\theta^*(x_4)$ can be solved from

$$\begin{aligned} & c(\beta_1 - 1)[\alpha(p\pi_g^H + (1-p)\pi_g^L - \pi_h) + \pi_h]((1-\alpha)^{\phi-1} \\ & + \beta_1 (p\pi_g^H + (1-p)\pi_g^L - \pi_h)(c + \tilde{c}(1-\alpha)^{\phi}) = 0. \end{aligned} \tag{15}$$

$$(\theta^*)^k [\frac{\beta_1}{k} - \beta_1 + 1] - (\theta^*)^{k-1}(\beta_1 - 1) + \beta_1 c = 0. \tag{16}$$

It is easy to verify that

$$\frac{\partial \alpha^*}{\partial p} > 0, \quad \frac{\partial \theta^*}{\partial p} = 0, \quad \frac{\partial \alpha^*}{\partial \sigma} < 0, \quad \frac{\partial \theta^*}{\partial \sigma} > 0. \tag{17}$$

$$\frac{\partial x_2}{\partial p} < 0, \quad \frac{\partial x_3}{\partial p} < 0, \quad \frac{\partial x_4}{\partial p} < 0, \quad \frac{\partial x_i}{\partial \sigma} > 0, \tag{18}$$

2.2. Model with switching option

2.2.1. Case 1: switch from strategy 1

In addition, firms frequently have the option to switch from 1 to 3 or 4. In this case, the firm value of strategy 1 is

$$\bar{V}_1(x) = \frac{\pi_h x}{r-\mu} + \bar{A}_i x^{\beta_1} + \bar{B}_i x^{\beta_2} - c - \tilde{c}, \tag{19}$$

where $i = \{2,3,4\}, \beta_1 = \frac{1}{2} - \frac{\mu}{\sigma^2} + \sqrt{(\frac{1}{2} - \frac{\mu}{\sigma^2})^2 + \frac{2r}{\sigma^2}} > 1$ and $\beta_2 = \frac{1}{2} - \frac{\mu}{\sigma^2} - \sqrt{(\frac{1}{2} - \frac{\mu}{\sigma^2})^2 + \frac{2r}{\sigma^2}} < 0$. I define the exit threshold $\bar{x}_i^e$ and the switching threshold $\bar{x}_i$ where $i = \{2,3,4\}$. With the proof in Appendix Appendix A.1, the solutions of the corresponding thresholds and arbitrary constants are obtained.

2.2.2. Case 2: switch from strategy 2

It is also possible that firms have the option to switch from 2 to 3 or 4 to enhance the monitoring of AI. In this case, the firm value of strategy 2 is

$$\hat{V}_2(x) = \frac{(p\pi_g^H + (1-p)\pi_g^L)x}{r-\mu} + \hat{A}_i x^{\beta_1} + \bar{B}_i x^{\beta_2} - c \tag{20}$$

where $i = \{3,4\}, \beta_1 = \frac{1}{2} - \frac{\mu}{\sigma^2} + \sqrt{(\frac{1}{2} - \frac{\mu}{\sigma^2})^2 + \frac{2r}{\sigma^2}} > 1$ and $\beta_2 = \frac{1}{2} - \frac{\mu}{\sigma^2} - \sqrt{(\frac{1}{2} - \frac{\mu}{\sigma^2})^2 + \frac{2r}{\sigma^2}} < 0$. I define the exit threshold $\hat{x}_i^e$ and the switching threshold $\hat{x}_i$where $i = \{3,4\}$. With the proof in Appendix Appendix A.2, the solutions of the corresponding thresholds and arbitrary constants are obtained.

2.2.3. Case 3: switch from strategy 3

Firms could also switch their strategy from strategy 3 to strategy 4. In this case, the firm value of strategy 3 is

$$\tilde{V}_3(x) = \alpha\frac{(p\pi_g^H + (1-p)\pi_g^L - \pi_h)x}{r-\mu} + \frac{\pi_h}{r-\mu}x + \tilde{A}_4 x^{\beta_1} + \tilde{B}_4 x^{\beta_1} - c - \tilde{c}(1-\alpha)^\phi \tag{21}$$

where $\beta_1 = \frac{1}{2} - \frac{\mu}{\sigma^2} + \sqrt{(\frac{1}{2} - \frac{\mu}{\sigma^2})^2 + \frac{2r}{\sigma^2}} > 1$ and $\beta_2 = \frac{1}{2} - \frac{\mu}{\sigma^2} - \sqrt{(\frac{1}{2} - \frac{\mu}{\sigma^2})^2 + \frac{2r}{\sigma^2}} < 0$. I define the exit threshold $\hat{x}_4$ and the switching threshold $\hat{x}_4$. With the proof in Appendix Appendix A.3, the solutions of the corresponding thresholds and arbitrary constants are obtained.

3. Results

I analyse the optimal strategy in the four work modes under the assumption that $r = 0.04, \mu = 0.01, \sigma = 0.2, \pi_h = 10, \pi_g^H = 10, \pi_g^L = 5, c = 3, \tilde{c} = 8, \phi = 2, k = 3$. If I fix $p = 0.5$ and $\sigma = 0.1$, the payoffs of different strategies are shown in Figure 1. The graph presented elucidates the relationship between market demand (denoted as x on the x-axis) and firms' value (depicted on the y-axis) across four distinct strategies. These strategies are: adopting human labour only (strategy 1), employing Gen-AI exclusively (strategy 2), distributing tasks between humans and Gen-AI (strategy 3), and utilizing a human-in-the-loop approach (strategy 4). The action thresholds for each strategy are marked as x_1, x_2, x_3, x_4, respectively. Different lines on the graph illustrate the firm's value against varying levels of market demand.

Figure 1 shows that the optimal strategy for firms is to implement the human-in-the-loop approach (strategy 4), as it has the lowest action threshold (x_4), suggesting it becomes viable at the lowest level of market demand. This strategy consistently provides superior value compared to the others, especially in scenarios of both low and high market demand. For low market demand, firms maximize their returns by employing Gen-AI exclusively (strategy 2), due to its relatively lower action threshold (x_2) and higher value compared to human labour alone (strategy 1). As market demand increases, strategy 3 (distributing tasks between humans and Gen-AI) becomes more advantageous than strategy 2, with the value line for strategy 3 surpassing that of strategy 2 at higher demand levels (x). This indicates that collaboration between humans and Gen-AI yields better outcomes as demand rises. Interestingly, the strategy of relying solely on human labour (strategy 1) is the least efficient in low demand scenarios, given its highest threshold (x_1) and lowest initial payoff. However, this strategy emerges as the most profitable when market demand becomes sufficiently high, outperforming both strategies 2 and 3. In contrast, strategy 3, while initially competitive, becomes the least optimal as market demand reaches higher levels. Overall, the findings suggest that rather than solely depending on Gen-AI, firms benefit

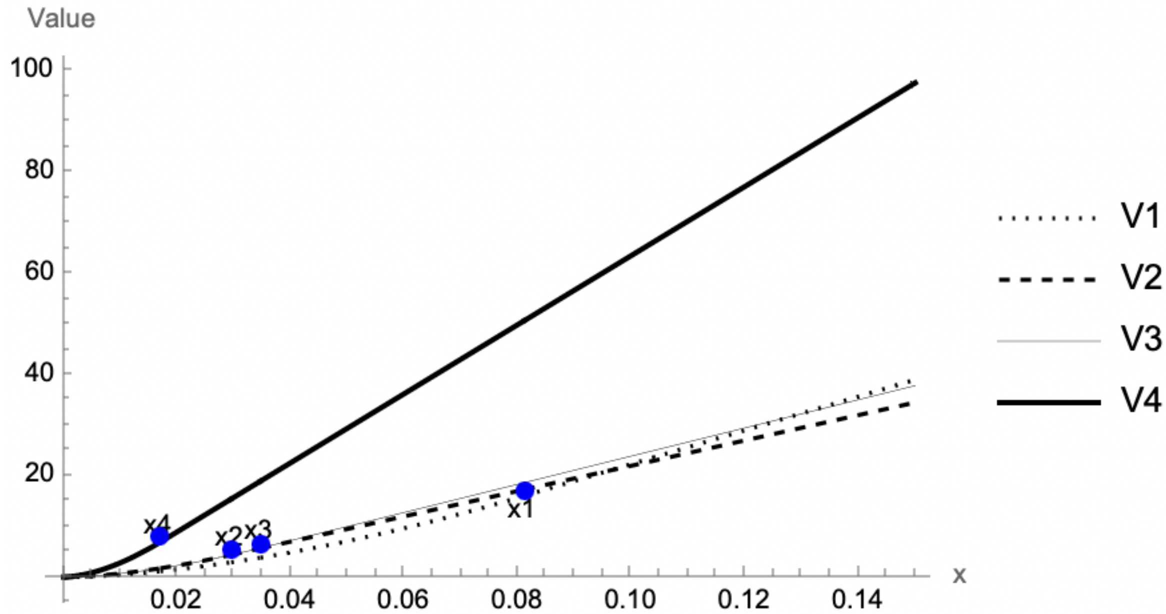


Figure 1: Payoffs of different strategies with x in baseline

more from integrating human input, particularly through a human-in-the-loop strategy. This collaborative approach consistently offers higher value across varying levels of market demand. Additionally, when demand is high, relying on human labour alone can yield the highest returns, whereas simply assigning tasks to Gen-AI becomes less effective. Thus, the strategic allocation of human and AI resources based on market demand is crucial for maximizing firm value.

3.1. The impact of Gen-AI performance uncertainty

In this section, I analyse how the uncertainty of Gen-AI performance affect firms' resources allocation and strategy decisions, particularly within contexts that harness both human expertise and AI capabilities.

The strategy thresholds are shown in Figure 2. The dotted line represents the threshold of the strategy that adopts humans only (x_1), The dashed line denotes the threshold of the strategy that adopts Gen-AI only (x_2), the thin solid line shows the threshold of the strategy that allocates tasks between Gen-AI and machine (x_2) and the thick solid line represents the threshold of the human in the loop strategy. Except for x_1, which remains constant

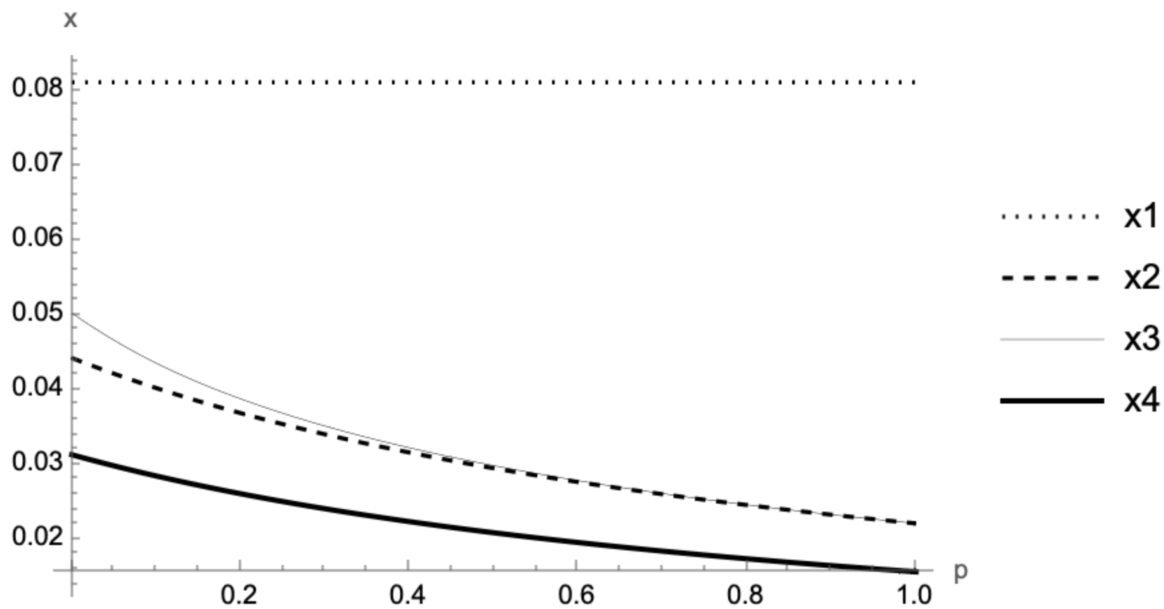


Figure 2: Strategy thresholds with p in baseline

with changes in p, the other thresholds exhibit a decreasing trend with increasing p. This suggests that the likelihood of achieving high-performance outcomes with Gen-AI leads to a faster adoption of strategies involving Gen-AI. Specifically, the figure shows that the threshold for strategy 4 is the lowest, indicating a predisposition towards adopting the human-in-the-loop strategy at the earliest opportunity, while the threshold for strategy 1 is the highest, suggesting a comparatively delayed adoption of this strategy relative to others. This observation aligns consistently with the observations from Figure 1.

Table 1 illustrates the optimal allocation proportion between Gen-AI and humans and improved efficiency with varying p in the baseline model. The result shows that the optimal proportion allocated to Gen-AI increases with the probability of high state performance of Gen-AI (p), and the threshold of improved efficiency is constant, which is consistent with Lemma 1. This indicates that with advancements in AI technologies and their increasing reliability (manifested in higher p values), organizations may gradually recalibrate their resource allocations towards Gen-AI. However, p do not substantially alter the overall efficiency improvement facilitated by human involvement in

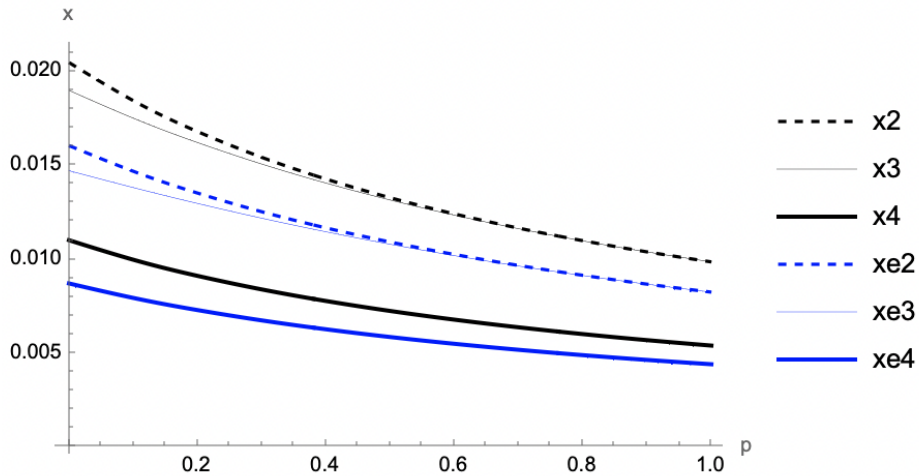
Table 1: Illustration of the optimal proportion ($\alpha^*(x_3)$) and improved efficiency ($\theta^*(x_4)$) as functions of the probability of high state performance of Gen-AI (p) in baseline

p	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
α^*	0.48	0.59	0.68	0.74	0.80	0.84	0.88	0.92	0.95	0.98	1
θ^*	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28	2.28

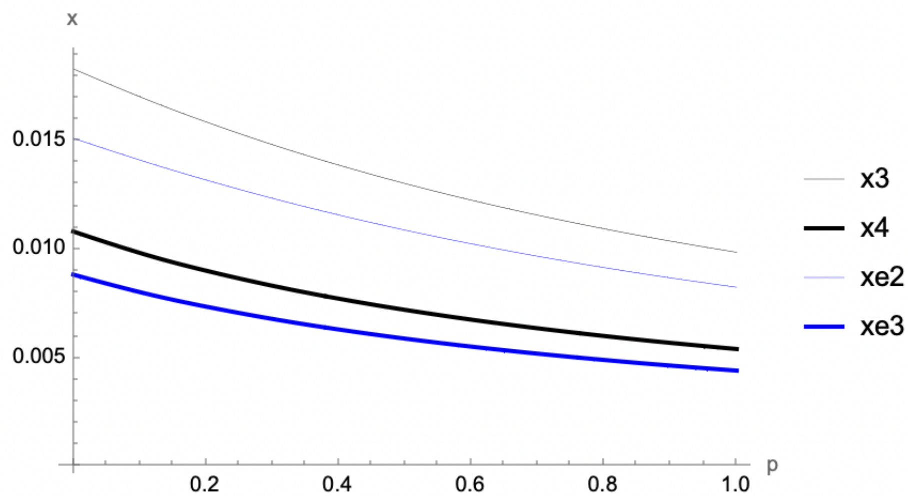
the human in the loop strategy.

Moreover, I then investigate if one of the strategies has been already adopted and firms would like to switch to another strategy. Figure 3 presents the switching threshold (x_i), which are depicted by black lines, and exit threshold (x_i^e), which are illustrated in blue. I first analyse the case 1 where a firm transitioning from strategy 1 to strategies 2, 3, and 4. Notably, all strategies exhibit a decreasing trend with respect to the probability (p), indicating that advancements in Gen-AI performance prompt an earlier transition to strategies involving Gen-AI. Furthermore, as p increases, the disparity between the exit threshold and the switching strategy diminishes for each strategy. This phenomenon suggests that as the likelihood of Gen-AI achieving high-performance outcomes rises, the gap between the point at which firms switch to a new strategy and the point at which they abandon the previous strategy becomes progressively narrower. This patterns exist for both case 2 and case 3 as shown in Figure 3b and 3c.

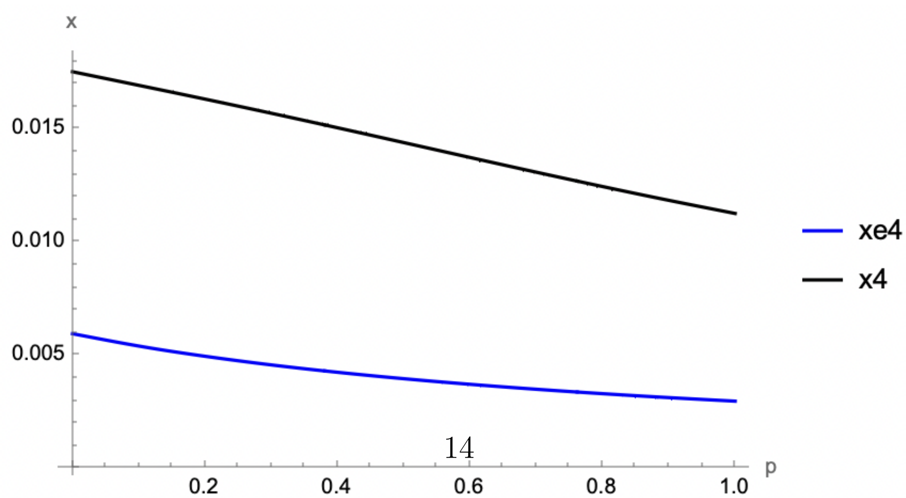
I further compare the optimal task allocation proportion ($\alpha^*(x_3)$) to Gen-AI and the corresponding enhancement factor ($\theta^*(x_4)$) attributed to human intervention, contingent upon the probability (p) of Gen-AI achieving high-performance outcomes in different scenarios as shown in Figure 4. Panel 4a demonstrates a positive correlation between the probability of Gen-AI achieving high-performance outcomes (p) and the optimal proportion of tasks assigned to Gen-AI (α^*). As p increases, firms tend to allocate a greater proportion of tasks to Gen-AI. Concurrently, Panel 4b illustrates that the enhancement factor (θ^*) resulting from human intervention experiences a slight decrease with increasing p except for the base case. This indicates that as the probability of high-performance outcomes by Gen-AI rises, the additional improvement attributed to human intervention diminishes marginally. When comparing different scenarios, the base case—where firms adopt one of the strategies 1, 2, 3, or 4 from no action—has the lowest α but the highest θ. The values of α and θ are very similar in case 1 (firms switch from strategy 1 to 2, 3, or 4) and case 2 (firms switch from strategy 2 to 3 or 4).



(a) Case 1

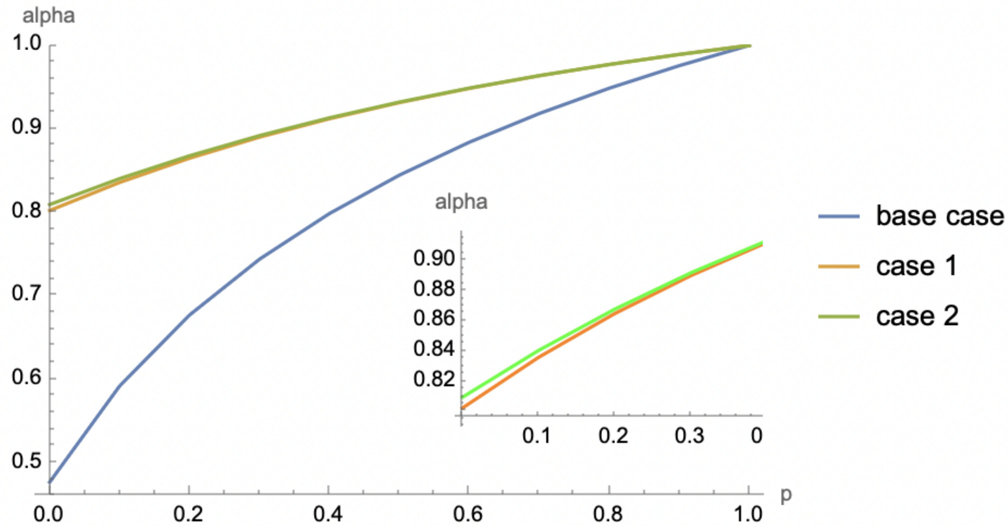


(b) Case 2

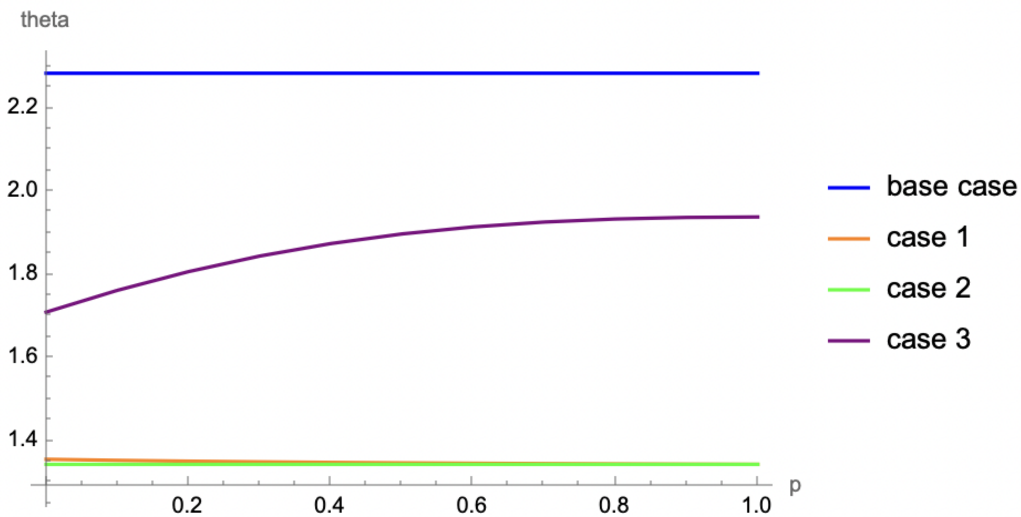


(c) Case 3

Figure 3: Strategy thresholds with p



(a)



(b)

Figure 4: The optimal proportion ($\alpha^*(x_3)$) and improved efficiency ($\theta^*(x_4)$) with the probability of high state performance of Gen-AI (p)

Overall, the impact of the probability (p) of achieving high-performance outcomes with Gen-AI reveals that as p increases, firms are more likely to adopt Gen-AI strategies earlier. This is reflected in the decreasing thresholds for strategy adoption and switching. Particularly, firms tend to adopt Gen-AI greater when allocating task between Gen-AI and humans as shown in ($\alpha^(x_3)$) with higher p, while the performance enhancement ($\theta^(x_4)$) provided by human intervention slightly decreases with higher p when firms switch their strategies.

3.2. The impact of market uncertainty

Figure 5 presents the relevant strategy thresholds with varying market volatility. The figure demonstrates that for all four strategies, the thresholds increase with market volatility (σ), suggesting that higher market uncertainty may hinder the adoption of these strategies. Significantly, the threshold for solely relying on human labor is the highest, whereas the threshold for the human-in-the-loop strategy is the lowest, consistent with previous observations. Additionally, the difference between the thresholds for task distribution between Gen-AI and humans (strategy 3) and the human-in-the-loop strategy (strategy 4) diminishes as σ increases.

If a firm has already adopted one strategy and wishes to switch to another, the switching threshold (x_i) and exit threshold (x_i^e) are depicted in Figure 6. The figure illustrates that the switching thresholds (x_i), represented by black lines, increase with market volatility (σ), while the exit thresholds (x_i^e), shown by blue lines, decrease with σ. This suggests that, similar to the base case, higher market volatility delays firms' decisions to adopt new strategies. However, it also reduces the likelihood of firms abandoning their current strategy. The threshold values remain relatively unchanged when comparing case 1 and case 2, but in case 3, the switching thresholds are notably higher, particularly under high market volatility. This indicates that switching from a strategy of task allocation between humans and Gen-AI to a human-in-the-loop strategy is less likely in volatile markets.

I also investigate the optimal task allocation proportion ($\alpha^*(x_3)$) to Gen-AI and the corresponding enhancement factor ($\theta^*(x_4)$) attributed to human intervention for different market volatility (σ) in different scenarios. The result is shown shown in Figure 7. Across all cases, the optimal task allocation proportion (α^*) decreases with increasing σ, indicating that firms allocate fewer tasks to Gen-AI as market volatility rises. Conversely, the enhancement factor (θ^*) attributed to human intervention increases with higher σ,

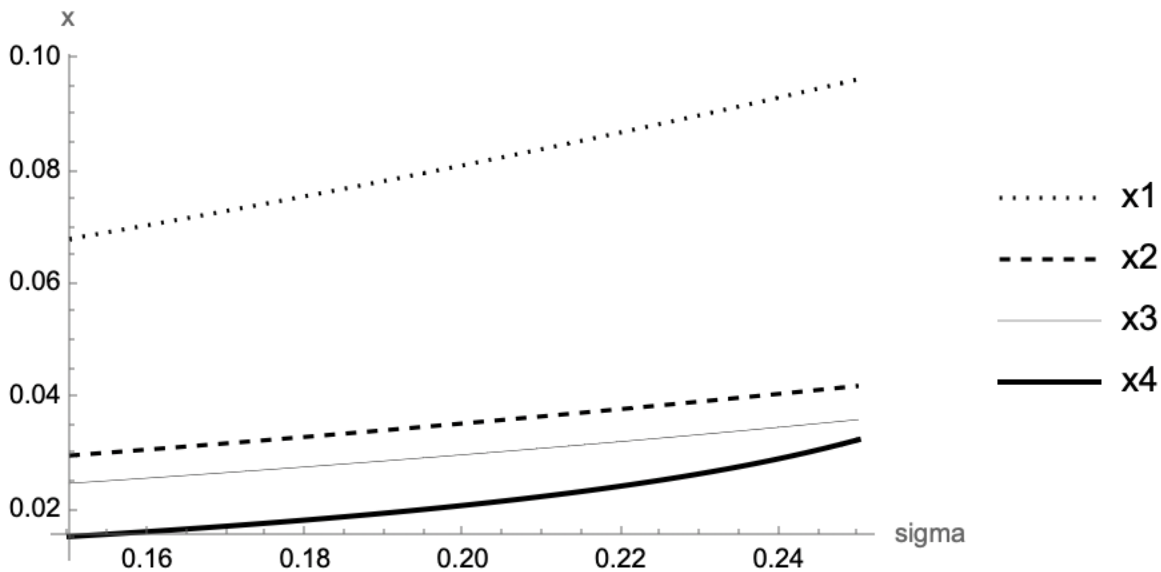
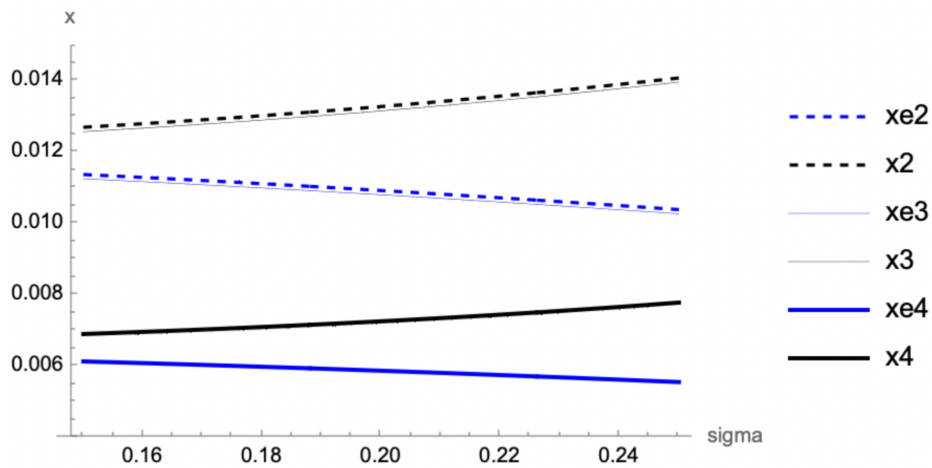


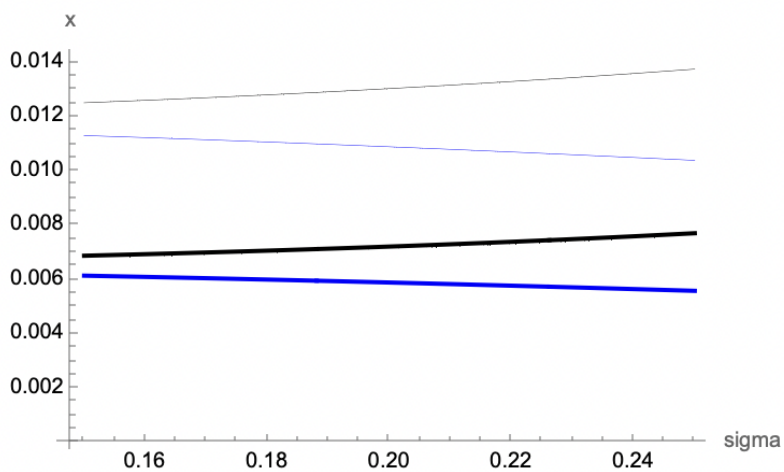
Figure 5: Strategy thresholds with σ in baseline

suggesting that human intervention becomes more important and requiring more human input in mitigating the effects of market volatility. Notably, the values of α^* and θ^* are closely aligned in case 1 and case 2, indicating similar strategic considerations in these scenarios. Overall, the findings underscore the dynamic interplay between market volatility and firms' strategic choices, highlighting the need for adaptive strategies in volatile environments.

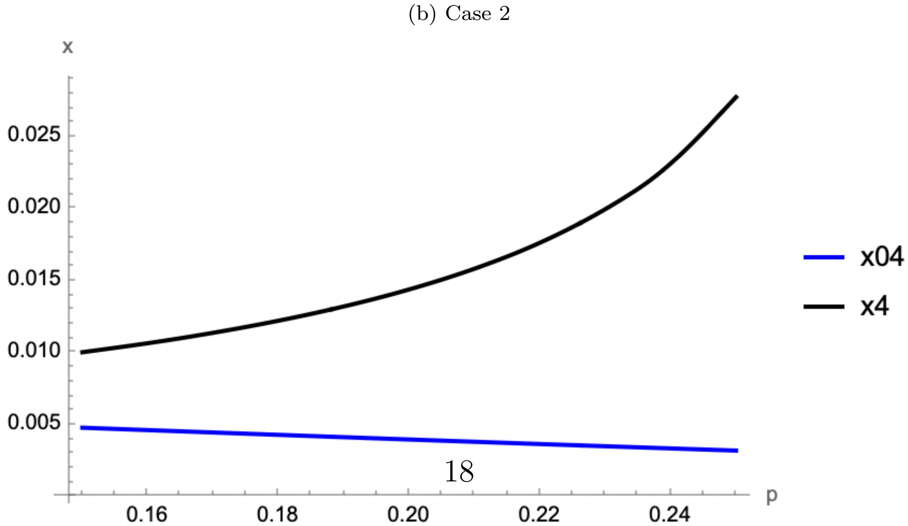
In general, higher probabilities of Gen-AI success prompt earlier adoption of Gen-AI-inclusive strategies, with increased reliance on Gen-AI and a slight reduction in the effectiveness of human intervention. Conversely, greater market volatility delays strategy transitions but enhances the value of human intervention while diminishing task allocation to Gen-AI. Notably, the findings highlight the importance of considering both Gen-AI performance and market uncertainties in strategic planning, as they significantly influence the optimal allocation of tasks and the effectiveness of human intervention across different strategic scenarios. Adaptive strategies that balance the strengths of Gen-AI and human capabilities are crucial for navigating uncertain and dynamic business environments effectively.



(a) Case 1

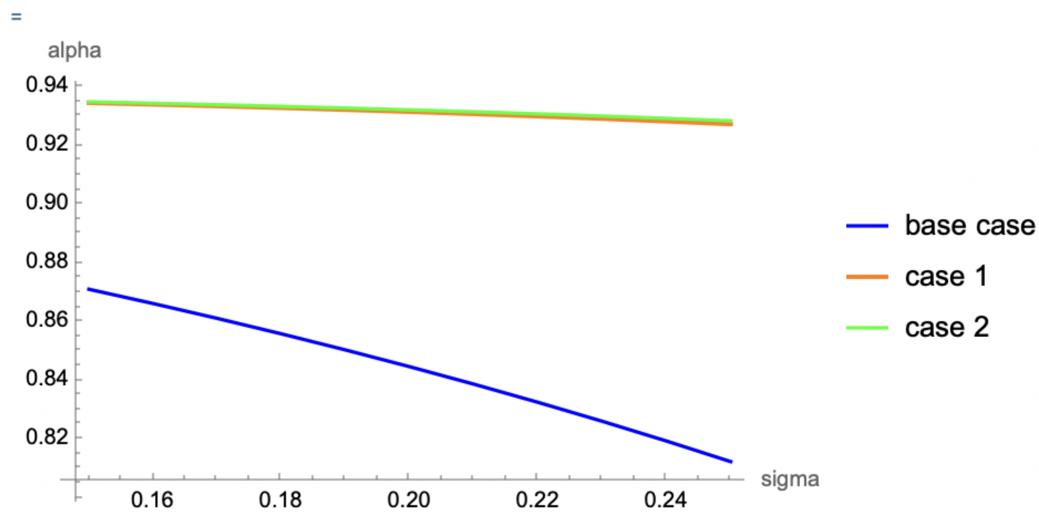


(b) Case 2

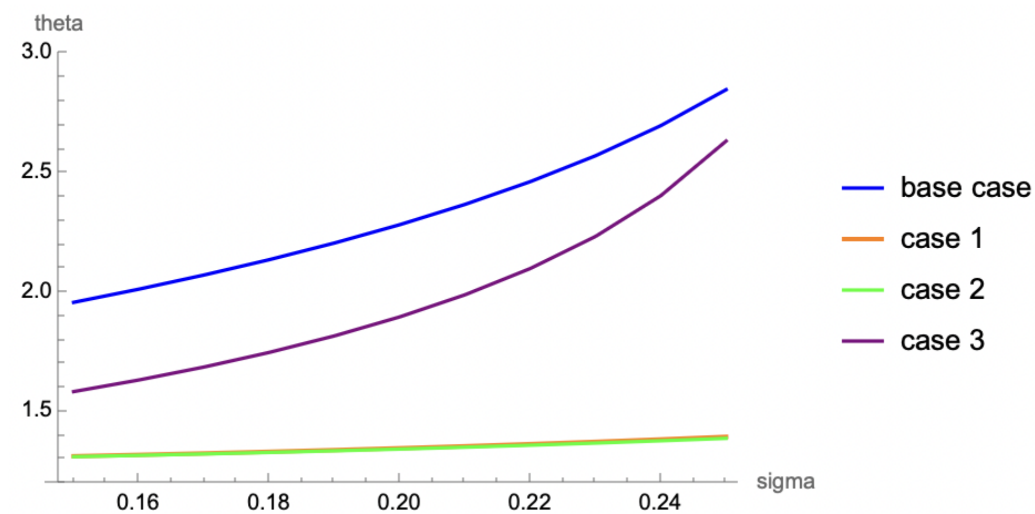


(c) Case 3

Figure 6: Strategy thresholds with σ



(a)



(b)

Figure 7: The optimal proportion ($\alpha^*(x_3)$) and improved efficiency ($\theta^*(x_4)$) with the market volatility (σ)

4. Conclusion

In this study, I developed a dynamic model to analyze the adoption of Generative Artificial Intelligence (Gen-AI) within the context of Gen-AI performance uncertainty and market uncertainty. I investigated the optimal collaboration strategies between Gen-AI and human labor, considering four distinct approaches based on Gen-AI involvement: exclusive AI participation, sole human involvement, task distribution between humans and AI, and the "Human in the Loop" approach aimed at enhancing AI performance with human intervention. The findings from our analysis shed light on the intricate dynamics of firms' strategic decision-making processes in the context of Gen-AI adoption and market volatility. The real options model employed in our study provides a robust framework for understanding how firms navigate uncertainties and make strategic choices over time. By accounting for various costs associated with humans and AI, diverse levels of Gen-AI performance, and the enhanced performance achievable through the "Human in the Loop" strategy, I argue against sole reliance on AI in all scenarios. Instead, I highlight the "Human in the Loop" strategy as consistently superior compared to alternative collaborative approaches.

Firstly, our analysis demonstrates the impact of the probability (p) of Gen-AI success on firms' thresholds for strategy adoption and exit. Higher probabilities of Gen-AI achieving high-performance outcomes lead to earlier adoption of Gen-AI-inclusive strategies, reflecting firms' growing confidence in Gen-AI capabilities. However, market volatility (σ) introduces complexities into this decision-making process. While higher volatility delays strategy transitions, it also enhances the value of human intervention, particularly in mitigating the effects of uncertainty.

Moreover, our study highlights the importance of balancing the allocation of tasks between Gen-AI and human intervention. As p increases, firms allocate a greater proportion of tasks to Gen-AI, but market volatility prompts a shift towards increased reliance on human intervention. This underscores the need for adaptive strategies that leverage the strengths of both Gen-AI and human capabilities to effectively navigate uncertain environments.

From a managerial perspective, our findings offer valuable insights for firms seeking to integrate Gen-AI into their operations. Managers must carefully consider both the performance potential of Gen-AI and the level of market volatility when making strategic decisions. Investing in Gen-AI technology is beneficial, but firms must also prioritize training and development initiatives to ensure that employees are equipped with the necessary skills to collaborate effectively with AI systems. Additionally, our study emphasizes the importance of continuous monitoring and adjustment of strategies in response to changing market conditions.

In conclusion, our study contributes to the literature by providing a comprehensive analysis of the impact of both Gen-AI success probabilities and market volatility on firms' strategic decision-making processes. The real options model employed offers a valuable tool for understanding and managing uncertainties in the adoption of emerging technologies like Gen-AI. By integrating these insights into their strategic planning processes, firms can effectively leverage Gen-AI to enhance decision-making and achieve sustainable competitive advantage in dynamic business environments.

In addition to the insights gained from this model, this study also points towards several promising avenues for future research in the field of Gen-AI adoption and strategic decision-making. One potential direction for future research is to delve deeper into the mechanisms underlying human-AI collaboration. Exploring how different forms of human intervention, such as feedback mechanisms or training programs, influence the performance and effectiveness of Gen-AI could provide valuable insights for optimizing collaborative approaches. Additionally, it is essential to explore the dynamics of competition between multiple firms operating in the same market under uncertainty. Investigating how competitive interactions influence the adoption and optimization of AI-human collaboration strategies would offer a comprehensive understanding of the strategic decision-making process in real-world scenarios.

Appendix A. Omitted proofs

Appendix A.1. Proof of case 1

Proof. With the boundary conditions:

$$\bar{V}_1(\bar{x}_i^e) = \frac{\pi_h \bar{x}_i^e}{r-\mu} + \bar{A}_i(\bar{x}_i^e)^{\beta_1} + \bar{B}_i(\bar{x}_i^e)^{\beta_2} - c - \tilde{c} = 0, \qquad \text{(value-matching at } \bar{x}_i^e) \tag{A.1}$$

$$\frac{\partial \bar{V}_1(\bar{x}_i^e)}{\partial \bar{x}_i^e} = \frac{\pi_h}{r-\mu} + \beta_1 \bar{A}_i(\bar{x}_i^e)^{\beta_1 - 1} + \beta_2 \bar{B}_i(\bar{x}_i^e)^{\beta_2 - 1} = 0, \qquad \text{(smooth-pasting at } \bar{x}_i^e) \tag{A.2}$$

$$\bar{V}_1(\bar{x}_i) = V_i(\bar{x}_i), \qquad \text{(value-matching at } \bar{x}_0) \tag{A.3}$$

$$\frac{\partial \bar{V}_1(\bar{x}_i)}{\partial \bar{x}_i} = \frac{\partial V_i(\bar{x}_i)}{\partial \bar{x}_i}. \qquad \text{(smooth-pasting at } \bar{x}_i) \tag{A.4}$$

Therefore, the unknown variables can be solved from the following equations:

(1)Switching to strategy 2

$$\frac{\pi_h \bar{x}_2^e}{r-\mu} + \bar{A}_2(\bar{x}_2^e)^{\beta_1} + \bar{B}_2(\bar{x}_2^e)^{\beta_2} - c - \tilde{c} = 0, \tag{A.5}$$

$$\frac{\pi_h}{r-\mu} + \beta_1 \bar{A}_2(\bar{x}_2^e)^{\beta_1 - 1} + \beta_2 \bar{B}_2(\bar{x}_2^e)^{\beta_2 - 1} = 0, \tag{A.6}$$

$$\frac{\pi_h \bar{x}_2}{r-\mu} + \bar{A}_2 \bar{x}_2^{\beta_1} + \bar{B}_2 \bar{x}_2^{\beta_2} - \tilde{c} = \frac{(p\pi_g^H + (1-p)\pi_g^L)\bar{x}_2}{r-\mu}, \tag{A.7}$$

$$\frac{\pi_h}{r-\mu} + \beta_1 \bar{A}_2 \bar{x}_2^{\beta_1 - 1} + \beta_2 \bar{B}_2 \bar{x}_2^{\beta_2 - 1} = \frac{p\pi_g^H + (1-p)\pi_g^L}{r-\mu}. \tag{A.8}$$

(2)Switching to strategy 3

$$\frac{\pi_h \bar{x}_3^e}{r-\mu} + \bar{A}_3(\bar{x}_3^e)^{\beta_1} + \bar{B}_3(\bar{x}_3^e)^{\beta_2} - c - \tilde{c} = 0, \tag{A.9}$$

$$\frac{\pi_h}{r-\mu} + \beta_1 \bar{A}_3(\bar{x}_3^e)^{\beta_1 - 1} + \beta_3 \bar{B}_3(\bar{x}_3^e)^{\beta_2 - 1} = 0, \tag{A.10}$$

$$\frac{\pi_h \bar{x}_3}{r-\mu} + \bar{A}_3 \bar{x}_3^{\beta_1} + \bar{B}_3 \bar{x}_3^{\beta_2} - \tilde{c} = \alpha \frac{p\pi_g^H + (1-p)\pi_g^L - \pi_h}{r-\mu}\bar{x}_3 + \frac{\pi_h \bar{x}_3}{r-\mu} - \tilde{c}(1-\alpha)^{\phi}, \tag{A.11}$$

$$\frac{\pi_h}{r-\mu} + \beta_1 \bar{A}_3 \bar{x}_3^{\beta_1 - 1} + \beta_2 \bar{B}_3 \bar{x}_3^{\beta_2 - 1} \tag{A.12}$$

$$= \alpha \frac{p\pi_g^H + (1-p)\pi_g^L - \pi_h}{r-\mu} + \frac{\partial \alpha}{\partial \bar{x}} \frac{(p\pi_g^H + (1-p)\pi_g^L - \pi_h)\bar{x}_3}{r-\mu} + \frac{\pi_h}{r-\mu} + \tilde{c}\phi(1-\alpha)^{\phi-1}\frac{\partial \alpha}{\partial \bar{x}}. \tag{A.13}$$

where α is defined in Equation (5).

(3)Switching to strategy 4

$$\frac{\pi_h \bar{x}_4^e}{r-\mu} + \bar{A}_4(\bar{x}_4^e)^{\beta_1} + \bar{B}_4(\bar{x}_4^e)^{\beta_2} - c - \tilde{c} = 0, \tag{A.14}$$

$$\frac{\pi_h}{r-\mu} + \beta_1 \bar{A}_4(\bar{x}_4^e)^{\beta_1 - 1} + \beta_2 \bar{B}_4(\bar{x}_4^e)^{\beta_2 - 1} = 0, \tag{A.15}$$

$$\frac{\pi_h \bar{x}_4}{r-\mu} + \bar{A}_4 \bar{x}_4^{\beta_1} + \bar{B}_4 \bar{x}_4^{\beta_2} - \frac{\theta^k}{k} = (1+\theta)\frac{p\pi_g^H + (1-p)\pi_g^L}{r-\mu}\bar{x}_4 - \frac{\theta^k}{k}, \tag{A.16}$$

$$\frac{\pi_h}{r-\mu} + \beta_1 \bar{A}_4 \bar{x}_4^{\beta_1 - 1} + \beta_2 \bar{B}_4 \bar{x}_4^{\beta_2 - 1} = (1+\theta)\frac{p\pi_g^H + (1-p)\pi_g^L}{r-\mu} + \frac{\partial \theta}{\partial \bar{x}} \frac{p\pi_g^H + (1-p)\pi_g^L}{r-\mu}\bar{x}_4 - \theta^{k-1}\frac{\partial \theta}{\partial \bar{x}}. \tag{A.17}$$

where θ is defined in Equation (6).

It is impossible to get an analytical solution for $\bar{A}_i$, $\bar{B}_i$, x_0 and x_2. Therefore, I show the numerical solutions instead. □

Appendix A.2. Proof of case 2

Proof. With the boundary conditions:

$$\hat{V}_2(\hat{x}_i^e) = \frac{(p\pi_g^H + (1-p)\pi_g^L)\hat{x}_i^e}{r-\mu} + \hat{A}_i(\hat{x}_i^e)^{\beta_1} + \hat{B}_i(\hat{x}_i^e)^{\beta_2} - c - \tilde{c} = 0, \qquad \text{(value-matching at } \hat{x}_i^e\text{)} \tag{A.18}$$

$$\frac{\partial \hat{V}_2(\hat{x}_i^e)}{\partial \hat{x}_i^e} = \frac{p\pi_g^H + (1-p)\pi_g^L}{r-\mu} + \beta_1\hat{A}_i(\hat{x}_i^e)^{\beta_1-1} + \beta_2\hat{B}_i(\hat{x}_i^e)^{\beta_2-1} = 0, \qquad \text{(smooth-pasting at } \hat{x}_i^e\text{)} \tag{A.19}$$

$$\bar{V}_2(\hat{x}_i) = V_i(\hat{x}_i), \qquad \text{(value-matching at } \hat{x}_0\text{)} \tag{A.20}$$

$$\frac{\partial \hat{V}_1(\hat{x}_i)}{\partial \hat{x}_i} = \frac{\partial V_i(\hat{x}_i)}{\partial \hat{x}_i}. \qquad \text{(smooth-pasting at } \hat{x}_i\text{)} \tag{A.21}$$

Therefore, the unknown variables can be solved from the following equations:
(1) Switching to strategy 3:

$$\frac{(p\pi_g^H + (1-p)\pi_g^L)\hat{x}_3^e}{r-\mu} + \hat{A}_3(\hat{x}_3^e)^{\beta_1} + \hat{B}_3(\hat{x}_3^e)^{\beta_2} - c - \tilde{c} = 0, \tag{A.22}$$

$$\frac{(p\pi_g^H + (1-p)\pi_g^L)}{r-\mu} + \beta_1\hat{A}_3(\hat{x}_3^e)^{\beta_1-1} + \beta_2\hat{B}_3(\hat{x}_3^e)^{\beta_2-1} = 0, \tag{A.23}$$

$$\hat{A}_3(\hat{x}_3)^{\beta_1} + \hat{B}_3(\hat{x}_3)^{\beta_2} - \tilde{c} = (1-\alpha)\frac{(\pi_h - p\pi_g^H - (1-p)\pi_g^L)}{r-\mu} - \tilde{c}(1-\alpha)^{\phi}, \tag{A.24}$$

$$\begin{aligned}\beta_1\hat{A}_3(\hat{x}_3)^{\beta_1-1} + \beta_2\hat{B}_3(\hat{x}_3)^{\beta_2-1} &= (1-\alpha)\frac{\pi_h - p\pi_g^H - (1-p)\pi_g^L}{r-\mu} \\ &+ \frac{\partial\alpha}{\partial\hat{x}}\frac{(p\pi_g^H + (1-p)\pi_g^L - \pi_h)\hat{x}_3}{r-\mu} + \tilde{c}\phi(1-\alpha)^{\phi-1}\frac{\partial\alpha}{\partial\hat{x}}.\end{aligned} \tag{A.25}$$

where α is defined in Equation (5).

(2) Switching to strategy 4:

$$\frac{(p\pi_g^H + (1-p)\pi_g^L)\hat{x}_4^e}{r-\mu} + \hat{A}_4(\hat{x}_4^e)^{\beta_1} + \hat{B}_4(\hat{x}_4^e)^{\beta_2} - c - \tilde{c} = 0, \tag{A.26}$$

$$\frac{(p\pi_g^H + (1-p)\pi_g^L)}{r-\mu} + \beta_1\hat{A}_4(\hat{x}_4^e)^{\beta_1-1} + \beta_2\hat{B}_4(\hat{x}_4^e)^{\beta_2-1} = 0, \tag{A.27}$$

$$\hat{A}_3(\hat{x}_3)^{\beta_1} + \hat{B}_3(\hat{x}_3)^{\beta_2} - \tilde{c} = \theta\frac{(p\pi_g^H + (1-p)\pi_g^L)\hat{x}_i}{r-\mu} - \frac{\theta^k}{k}, \tag{A.28}$$

$$\beta_1\hat{A}_4(\hat{x}_4)^{\beta_1-1} + \beta_2\hat{B}_4(\hat{x}_4)^{\beta_2-1} = \theta\frac{p\pi_g^H + (1-p)\pi_g^L}{r-\mu} + \frac{\partial\theta}{\partial\hat{x}}\frac{p\pi_g^H + (1-p)\pi_g^L}{r-\mu}\hat{x}_4 - \theta^{k-1}\frac{\partial\theta}{\partial\hat{x}}. \tag{A.29}$$

□

Appendix A.3. Proof of case 3

Proof. With the boundary conditions:

$$\alpha\frac{(p\pi_g^H + (1-p)\pi_g^L - \pi_h)\tilde{x}_4^e}{r-\mu} + \frac{\pi_h\tilde{x}_4^e}{r-\mu} + \tilde{A}_4(\tilde{x}_4^e)^{\beta_1} + \tilde{B}_4(\tilde{x}_4^e)^{\beta_2} - c - \tilde{c}(1-\alpha)^{\phi} = 0, \tag{A.30}$$

$$\alpha\frac{p\pi_g^H + (1-p)\pi_g^L - \pi_h}{r-\mu} + \frac{\partial\alpha}{\partial\tilde{x}_4^e}\frac{(p\pi_g^H + (1-p)\pi_g^L - \pi_h)\tilde{x}_4^e}{r-\mu} + \frac{\pi_h}{r-\mu} + \beta_1\tilde{A}_4(\tilde{x}_4^e)^{\beta_1-1} + \beta_2\tilde{B}_4(\tilde{x}_4^e)^{\beta_2-1} = 0, \tag{A.31}$$

$$\tilde{A}_4(\tilde{x}_4)^{\beta_1} + \tilde{B}_4(\tilde{x}_4)^{\beta_2} - \tilde{c}(1-\alpha)^{\phi} = (1-\alpha)\frac{(p\pi_g^H + (1-p)\pi_g^L - \pi_h)\tilde{x}_4}{r-\mu} + \theta\frac{(p\pi_g^H + (1-p)\pi_g^L)\tilde{x}_4}{r-\mu} - \frac{\theta^k}{k} \tag{A.32}$$

$$\begin{aligned}\beta_1\tilde{A}_4(\tilde{x}_4)^{\beta_1-1} + \beta_2\tilde{B}_4(\tilde{x}_4)^{\beta_2-1} + \tilde{c}\phi(1-\alpha)^{\phi-1}\frac{\partial\alpha}{\partial\tilde{x}_4} &= (1-\alpha)\frac{p\pi_g^H + (1-p)\pi_g^L - \pi_h}{r-\mu} \\ - \frac{\partial\alpha}{\partial\tilde{x}_4}\frac{(p\pi_g^H + (1-p)\pi_g^L - \pi_h)\tilde{x}_4}{r-\mu} + \theta\frac{p\pi_g^H + (1-p)\pi_g^L}{r-\mu} &+ \frac{\partial\theta}{\partial\tilde{x}_4}\frac{(p\pi_g^H + (1-p)\pi_g^L)\tilde{x}_4}{r-\mu} - \theta^{k-1}\frac{\partial\theta}{\partial\tilde{x}_4}.\end{aligned} \tag{A.33}$$

Therefore, the unknown variables can be solved from the above equations. □

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