Journal of Industrial and
Management Optimization

https://www.aimspress.com/journal/jimo

JIMO, 22(3): 1244–1283.
DOI:10.3934/jimo.2026046
Received: 25 July 2025
Revised: 15 January 2026
Accepted: 30 January 2026
Published: 09 February 2026

Research article

Quality upgrade strategies in a supply chain with advanced disclosure under AI technology

Qi Zheng and Keke Xie*

School of Management, Shanghai University of Engineering Science, Shanghai 201620, China

* **Correspondence:** Email: 15538897124@163.com.

Abstract: This study develops a two-period supply chain model consisting of a supplier, a retailer, and consumers to explore the interplay between artificial intelligence (AI)-driven quality upgrades and information disclosure strategies. The supplier decides on the level of AI-driven quality upgrade, while the retailer determines whether to disclose the product's quality information. The results indicate that AI upgrades by the supplier should only be implemented when the resultant performance improvement surpasses a critical threshold, effectively offsetting the associated costs; marginal upgrades should be deferred to prevent potential profit erosion. Conversely, retailers should disclose the product's quality information when consumer quality preference is high or when uncertainty regarding product quality is low. In situations of high uncertainty, retailers are advised to withhold information to discourage strategic waiting by consumers. Furthermore, when AI investment is endogenously determined within the Bayesian trust-updating framework, information disclosure not only enhances market transparency but also activates a trust-amplification feedback loop, which significantly strengthens the supplier's investment incentives by boosting the perceived value of AI-driven quality improvements. Notably, dual-rollover strategies are shown to yield higher profitability at both extremely low and extremely high AI upgrade levels, while single-rollover strategies demonstrate superior performance at moderate upgrade levels. These findings offer actionable insights for aligning AI investment, pricing strategies, and disclosure decisions. They also provide policy guidance for the design of balanced AI subsidies and transparency frameworks, thereby promoting sustainable supply chain innovation.

Keywords: AI technology; advanced disclosure; quality upgrade; rollover approach; multi-period decision-making
Mathematics Subject Classification: 90B06, 91A35

1. Introduction

With global high-quality development and advancing digital transformation, data-driven technologies have gained wider adoption across industries. As a core representative of such technologies, artificial intelligence (AI) is being widely applied by enterprises in production operations and strategic decision-making, emerging as a vital engine for industrial upgrading and efficiency enhancement. AI technology has significantly transformed numerous industries, with profound implications for enhancing product quality. AI empowers manufacturers to elevate product quality through real-time data analytics, process automation, and sophisticated monitoring systems. These AI-driven systems facilitate dynamic quality control, thereby improving the products' performance and reliability, particularly in sectors such as smart home appliances, electronics, and automotive components. AI's capacity to optimize production processes and enhance the responsiveness of supply chains to evolving consumer demands establishes it as an indispensable tool for advancing product quality.

As living standards increase, consumers increasingly demand precise and timely product quality information before making purchasing decisions, thereby intensifying the pressure on firms to ensure effective disclosure. Nevertheless, enterprises frequently encounter challenges stemming from insufficient transparency, including delayed product announcements and inadequate quality disclosures. For novel products, especially in rapidly evolving sectors like smart home appliances, consumers seek detailed, reliable information regarding the products' attributes such as energy efficiency, smart control precision, and durability. However, firms often fail to provide comprehensive specifications upfront, leading to consumer hesitation and market inefficiencies. For instance, Samsung's 2023 Neo QLED TV launch experienced a 22% decline in pre-orders compared with projections, attributable to the delayed release of crucial panel specifications, particularly those related to AI-driven dynamic contrast adjustments. Consequently, consumers deferred their purchases, awaiting clarification. These instances underscore how suboptimal disclosure practices can distort consumers' decisions and negatively impact firms' performance. The problem becomes particularly acute when AI technology is involved, as consumers recognize that AI capabilities can significantly affect the product's performance but often lack clear information about the nature and extent of these improvements.

As a representative data-driven technology, AI offers an innovative solution to these challenges by improving the timeliness and comprehensiveness of product quality information disclosures. In this study, AI assumes two pivotal and interconnected roles. First, it serves as an enabler of process innovation that drives substantive quality improvements through data-driven optimization, predictive maintenance, and adaptive manufacturing systems. Second, it functions as a facilitator of information transparency that enables credible, timely, and verifiable disclosure of a product's quality attributes. These dual roles create a synergistic relationship in which AI-driven quality improvements generate valuable information that can be disclosed, while AI-enhanced disclosure mechanisms increase consumers' trust in the quality claims, potentially amplifying the market value of the technological improvements.

In recent years, a growing number of enterprises have recognized the synergistic dual roles of AI technology, which are empowering quality upgrades and facilitating credible advanced disclosure. Tesla's full self-driving system serves as a typical case. Its AI algorithms not only substantially enhance driving safety and ride smoothness, acting as the enabler to drive quality improvement and also generate real-time visualized data and safety scores that provide credible evidence for advanced disclosure, playing the facilitator role. Similarly, Apple's computational photography leverages AI to achieve leaps in image quality such as Night mode. The underlying AI-driven process generates detailed performance metrics that can be transparently communicated to the consumers. Therefore, AI technology concurrently drives core product improvement and generates verifiable information, which is necessary for effective advanced disclosure. This perfectly embodies the interconnected functionality that is central to our model.

Our research framework explicitly models this dual functionality of AI within a supply chain context. We examine how the interplay between AI-driven quality upgrades and AI-facilitated information disclosure affects strategic decision-making across supply chain tiers. While our analysis is firmly grounded in the AI context, given its technological prominence and growing economic significance, the theoretical insights we develop regarding the relationship between technology adoption, information credibility, and consumer behavior have broader applicability. The core mechanisms we examine are relevant to a wider class of digital and data-driven technologies that improve both product performance and information reliability. Examples include Internet of Things systems for quality tracking and blockchain solutions for supply chain transparency. We select AI as our primary analytical focus precisely because it embodies both capabilities in a particularly pronounced and managerially relevant manner.

Specifically, suppliers leverage AI technology to determine whether to implement product quality upgrades and to determine the optimal level of such enhancements, thereby optimizing the overall product quality. Conversely, retailers utilize AI technology to decide whether to disclose quality information pertaining to the upgraded product, focusing on specifications, test results, and reliability data. These two aspects are managed by distinct entities within the supply chain, and the dual functionality of AI technology not only influences the product's quality control but also plays a critical role in augmenting information transparency.

For example, Lenovo integrated an AI-driven quality tracking system into its ThinkPad production lines, enabling dynamic disclosure of the durability test results and the components' reliability metrics. This technological intervention resulted in a 22% increase in pre-order conversion rates, as consumers gained access to more detailed and current quality information. Furthermore, governmental policies globally are actively promoting such AI applications in manufacturing. For instance, China's Intelligent Manufacturing Development Plan allocates funding for AI-driven quality information systems, while the EU's Digital Industry Act offers tax incentives to manufacturers adopting real-time quality disclosure technologies.

Governmental policy support has emerged as a critical catalyst for AI's adoption in manufacturing, yet significant implementation challenges persist. Initiatives like the US CHIPS and Science Act, which subsidizes 25% of AI industrial equipment's costs, have propelled the adoption of predictive maintenance to 42% in the automotive sector. Nevertheless, manufacturers continue to face escalating costs associated with AI-driven upgrades. These policy incentives have introduced a complex dynamic: They accelerate AI's adoption while simultaneously intensifying competitive pressures across supply chains. These incentives have generated tensions between technological advancement and the equitable distribution of costs and benefits across the ecosystem. Nonetheless, the global intelligent manufacturing market continues its rapid expansion, with projections indicating a 24.5% compound annual growth rate (CAGR) through to 2030, where AI-driven quality enhancements already account for 38% of premium product margins in electronics [1].

However, the implementation of AI technology not only increases an enterprise's costs but also accelerates the product upgrading cycle. Despite policy support, substantial cost challenges associated with AI-driven upgrades remain. Enterprises confront a critical resource allocation dilemma when initiating upgrades. They must choose between extending the lifecycle of existing products or investing in next-generation offerings amidst the escalating costs of AI-driven quality upgrades and heightened competitive pressures. Such challenges, including the cost of AI-driven quality upgrades and potential competition between older and newer product versions, may impede firms from executing product upgrades. Concurrently, consumers' strategic waiting behavior significantly impacts the supply chain's profitability. As evidenced in the Apple case, purchase delays due to expected upgrades substantially affect revenue. Thus, we investigate whether advanced information disclosure can mitigate this behavior.

With advancements in AI technology and evolving consumer expectations, product upgrade cycles are accelerating rapidly. When executing upgrades, product rollover approaches introduce further complexity into supply chain decisions. Firms typically utilize one of two primary product rollover strategies: single or dual rollover. A single-rollover approach involves completely phasing out the existing products, with the supply chain exclusively providing upgraded products in the subsequent period. This approach is particularly prevalent in the automotive and consumer electronics industries; as Sekar [2] demonstrates, Sony systematically phases out older PlayStation models upon new console launches to maintain brand premiumization. Conversely, a dual-rollover strategy permits both legacy and upgraded products to coexist in the market [3]. This approach is commonly employed in the personal computer and home appliance sectors. Samsung strategically maintains previous Galaxy smartphone models alongside new releases, while Dell concurrently offers multiple generations of laptop configurations. However, this approach introduces potential competition between product versions, necessitating careful evaluation of dual revenue streams against possible cannibalization effects, particularly when AI-driven quality improvements create significant differentiation between product generations.

Building upon the aforementioned context, our research examines how firms can optimize decisions regarding AI-driven quality upgrades, information disclosure strategies, and rollover approaches while addressing upgrade costs, consumers' strategic behavior, and profit distribution challenges. Our study contributes four principal theoretical advancements: First, we develop four game-theoretic scenarios capturing the supplier's AI-adoption decision and the retailer's pre-emptive disclosure choice. Second, we incorporate forward-looking consumers and product transition strategies to quantitatively evaluate their impact on the optimal transition mode selection. Third, we establish quantitative linkages between AI-driven quality upgrade levels and profit distribution across supply chain tiers. Fourth, we introduce an analytical framework to examine supply chain-related decision-making under asymmetric information during AI-driven upgrades. Furthermore, our research makes an important conceptual contribution by clarifying the boundary conditions of AI-specific insights versus more generalizable principles. While we employ AI as our motivating technological context and explicitly model AI-specific mechanisms such as trust-enhanced disclosure credibility, our findings regarding the optimal coordination of technology investment and the information strategy have relevance for various digital technologies that enhance both product performance and information transparency. We position our work at the intersection of technology management and information economics. We use AI as a particularly salient example of technologies that transform both what firms produce and how they communicate about their products. Consequently, our research addresses the following four questions:

RQ 1. Should the retailer choose advanced disclosure of the quality of product upgrades with AI technology in the second period?

RQ 2. Under what conditions is the supplier willing to adopt the quality upgrades with AI technology in the second period?

RQ 3. What strategies should supply chain members adopt under different rollover approaches in the context of the quality upgrades with AI technology?

RQ 4. How does endogenous AI investment influence suppliers' upgrade decisions, and how is it affected by retailers' disclosure behavior?

To address these research questions, this study investigates how quality disclosure, product upgrade strategies, and consumers' strategic waiting behavior influence supply chain members' decision-making. We examine the impact of these factors on their product upgrade decisions, information disclosure approaches, and market performance, with the aim of providing theoretical references and actionable insights for scientific formulation of the supply chain strategy. Furthermore, the research develops a game-theoretic model to analyze interactions between product upgrades and quality disclosure within a supply chain setting.

The subsequent sections are structured as follows. Section 2 provides a systematic review of the relevant literature. Section 3 introduces the problem's description and notation, detailing the two-period supply chain structure, the four scenarios (LN, LD, HN, HD) based on the supplier's upgrade decision and the retailer's disclosure choice, along with definition of the key parameter. Section 4 develops the model's formulation and solution approach, applying Stackelberg game theory to derive equilibrium outcomes. Section 5 analyzes disclosure and upgrade strategies and their impacts, conducting sensitivity analyses and comparing equilibrium results across the four scenarios. Section 6 examines the dual-rollover strategy, introducing Scenarios HND and HDD, where legacy and upgraded products coexist in the second period, and compares them with single-rollover strategies. Section 7 extends the analysis by considering endogenous AI investment levels. This extension incorporates a trust-based belief updating mechanism that captures how AI investment enhances the credibility of quality disclosures. This provides a more nuanced understanding of the relationship between technology adoption and information transparency. Finally, Section 8 concludes the study and suggests avenues for future research.

2. Literature Review

Our research is primarily related to three areas of the literature: (i) Quality disclosure, (ii) product upgrades in the context of forward-looking consumers, and (iii) the product rollover approach. Next, we briefly review the literature for each and describe how our work relates to it.

2.1. Quality disclosure

Recently, scholarly research addressing quality disclosure in supply chains has garnered a great deal of attention and is abundant within the academic community. The existing literature has explored whether or not firms should reveal their products' quality to consumers. Initial studies explored the role of quality differentiation, where Zhao et al. [4] demonstrated that disclosure strategies for firms in competitive markets critically depend on consumers' prior quality beliefs, while Li et al. [5] identified a boost in first-period sales for high-quality technology firms disclosing when the quality differences are small. Zheng et al. [1] also established that product unreliability and high innovation costs reduce the disclosure likelihood for risk-averse firms, and Liu et al. [6] linked earlier retailer disclosure to mitigating cannibalization during high-innovation product upgrades. Beyond the inherent product characteristics, the research scope has broadened to analyze supply chains' cost structures. Here, Yu et al. [7] documented how demand asymmetry inhibits disclosure in food supply chains, though cost-effective freshness services can incentivize sharing, and Jiang et al. [8] specifically associated high disclosure costs with suppliers' preference for their own disclosure scenario under low market entry costs. Subsequently, investigations extended to the complexities of supply chain collaboration and conflicting incentives. Hao and Tan [9] observed misaligned supplier-retailer disclosure incentives under wholesale pricing when consumers' valuation dispersion is moderate. Wu et al. [10] connected platform entry to increased manufacturer disclosure, whereas Yu et al. [11] indicated potential increases in retailer competition following high-quality product disclosure. Finally, Menezes et al. [12] examined disclosure as a strategic response to channel conflict, revealing that retailers' use of disclosure can deter supplier encroachment, contrasting with the suppliers' preferences under specific cost conditions. Current studies predominantly focus on product quality differentiation, supply chains' operational costs, and collaboration dynamics. However, there has been limited exploration of how product upgrade decisions and selection of the rollover strategy influence downstream retailers' disclosure strategies. Additionally, the influence of advanced disclosure on consumers' strategic waiting behavior during product transitions has not been extensively examined. This paper expands the existing literature by considering the interconnections among product upgrades, rollover strategies, and the timing and nature of disclosure strategies, with a particular focus on how these elements influence consumer behavior.

2.2. Product upgrades

The existing literature relevant to our study focuses on product upgrades, encompassing consumers' psychology, strategic implementation, pricing dynamics, and supply chain coordination. Research into consumers' perceptions has revealed that upgrades can trigger feelings of abandonment among existing users [13], an effect that personalized services can mitigate. Specifically, Garbas et al. [14] found that internal upgrades involving tangible changes elicit heightened negative reactions. Furthermore, Wiegand and Imschloss [15] demonstrated lower consumer receptiveness to software upgrades compared with hardware upgrades, although bundling strategies and emphasizing low integration costs can improve acceptance. Building on this understanding of consumers' psychology, subsequent research has addressed strategic implementation. For instance, Kash et al. [16] determined that cyclical upgrades are optimal post-launch for subscription services, necessitating coordinated pricing strategies. Studies have also examined rollover strategies within trade-in programs. Yang et al. [17] found that a single rollover outperforms alternative strategies when consumers behave strategically, while Schwarz and Tan [18] linked production capacity constraints to hybrid rollover approaches, observing non-monotonic relationships between capacity levels and strategy selection. The strategic complexity of upgrades also necessitates examining their effects on pricing and supply chain coordination. Wang et al. [19] demonstrated that while direct quality improvements tend to reduce selling prices, trade-in programs exert countervailing upward pressure. Dong et al. [20] associated product diffusion rates with the timing of suppliers' technology investment. Srivastava et al. [21] highlighted how upgrades can intensify gray market diversion, though manufacturers can leverage price adjustment flexibility to enhance profitability, especially with significant upgrades and strong brand equity. Huang et al. [22] suggested that high-quality firms risk market share erosion from substitution effects during upgrades, in contrast to the potential stability for low-quality firms. While previous studies have explored consumer behavior, the optimal timing of quality upgrades, pricing dynamics, and supply chain coordination, limited attention has been paid to the role of AI technology in driving product quality upgrades and how advanced disclosure influences upgrade decisions. Our research extends this literature by investigating the role of AI in driving quality upgrades and its interaction with disclosure strategies, as well as how these factors impact consumer behavior during product upgrades.

2.3. Product rollover approach

Existing research on dual-rollover strategies identifies key determinants across three interconnected dimensions: The product's innovation level, consumers' strategic behavior, and supply chain collaboration within multi-stage competition. The product's innovation level fundamentally shapes the optimal rollover selection. For instance, Ye et al. [23] established that low innovation levels favor dual-rollover strategies depending on consumer discounting factors, whereas high innovation favors a single rollover. This innovation-dependent calculus extends to uncertain environments, where dual rollover serves as a risk-hedging mechanism under high firm-level risk aversion and demand uncertainty [24]. Building upon these considerations of innovation, consumers' strategic behavior emerges as a pivotal moderator. Liu et al. [25] identified that the rollover strategy depends critically on the innovation level, salvage value, and strategic consumer behavior. To optimize outcomes with strategic consumers, Xiao et al. [26] recommended early upgrade program deployment alongside late-stage price reduction strategies near new product launches. Extending beyond firm-level decisions, supply chain coordination and competitive dynamics necessitate integrated rollover planning. Bae et al. [27] revealed that product deletion decisions (inherent in rollover) significantly impact upstream and downstream stakeholders across the supply chain. Wu and Lai [28] explicitly modeled multi-stage competition, concluding that the rollover strategy significantly influences profitability under asymmetric competition, necessitating dynamic adjustments in pricing and launch timing according to the evolution of market demand. Despite the emphasis in the existing literature on product innovation levels, consumers' strategic behavior, and supply chain coordination in determining the optimal rollover strategy, the interaction between rollover strategies and quality disclosure remains largely unexplored. Specifically, the effect of advanced disclosure in mitigating consumers' strategic waiting behavior during upgrades has not been thoroughly examined. Our study aims to provide a more comprehensive understanding by considering the role of disclosure in the context of both rollover strategies and product upgrades.

2.4. Research gap

Table 1 summarizes the literature and compares it with our research. A review of the existing studies reveals the following. (i) Despite substantial attention to quality disclosure, product upgrades, and rollover strategies as separate domains, the causal interdependencies between these decisions have not been comprehensively explored. (ii) Prior research has not systematically examined how early quality disclosure can serve as a strategic tool to mitigate consumers' waiting behavior during product transitions. This study contributes by establishing an integrated framework that connects product upgrades, quality disclosure, and rollover strategies, with a particular focus on AI-driven quality upgrades. Specifically, we examine how AI technology influences product quality upgrades and how early disclosure decisions interact with rollover strategies. Our framework offers new insights into how these decisions interact and affect consumer behavior in the context of product transitions within technology-intensive supply chains.

Table 1. Research gaps between the literature and study.

Reference	Year	Quality disclosure	Product upgrade	Rollover strategy	Strategic customers
Liu et al.	2018			✓	
Zhao et al.	2018	✓			
Wu et al.	2019	✓			
Hao et al.	2019	✓			✓
Ye et al.	2020		✓	✓	✓
Wiegand et al.	2021	✓	✓		✓
Schwarz et al.	2021		✓	✓	✓
Niu et al.	2022	✓	✓	✓	
Menezes and Pinto	2022		✓		
Jung et al.	2022	✓	✓		
Zheng et al.	2023	✓	✓		✓
Kash et al.	2023	✓	✓		✓
Wang et al.	2023		✓		
Dong et al.	2023		✓		✓
Yang et al.	2023			✓	✓
Wu et al.	2023	✓	✓		
Jiang et al.	2023	✓			
Garbas et al.	2023	✓	✓	✓	
Li et al.	2024		✓		✓
Liu et al.	2024	✓	✓	✓	
Srivastava et al.	2024		✓		✓
Xiao et al.	2024		✓	✓	
Yu et al.	2024	✓			
Bae et al.	2024		✓		✓
Huang et al.	2025		✓		✓
Our study		✓	✓	✓	✓

3. Description of the Problem and Notations

We consider a supply chain comprising one supplier and one retailer, where the retailer purchases products from the supplier and sells them to consumers over two periods. The problems are described as follows, and we summarize all notation in Table 2.

In the first period, the supplier sells a product with lower quality (denoted as m_L), and in the second period, the supplier chooses to continue selling the same product or to upgrade it to a higher quality level using AI technology. We assume that the quality of the low-quality product is upgraded to m_H $(m_H = km_L)$ after adopting AI technology. Referring to the study by Zheng and Brintrup [29] and Zhu et al. [30], we assume that the total cost of adopting AI technology is a quadratic function of the investment level, that is $c_k = \frac{1}{2}tk^2$, where k denotes the AI technology investment coefficient. This convex cost structure reflects the increasing marginal costs of developing AI capability. The supplier's upgrade decision is transparent to the retailer, who then decides whether to disclose the quality of the next-period product to consumers. Due to the information asymmetry between the retailer and consumers, the retailer has more detailed knowledge about the product's quality. The retailer can choose to use AI technology to provide advanced disclosure of the true quality of the next-period product. For simplicity, we assume that this disclosure, if made, is complete, meaning that the consumers gain full access to the product's actual quality. While AI-driven quality disclosure allows consumers to access accurate product quality information, such technology might raise consumers' concerns about potential privacy leakage. However, as this is not the focus of the current study, we abstract away from considerations of privacy worries in our model.

In this paper, we assume that the consumers are aware of the current period's product quality but are uncertain about the quality of the subsequent product. In the absence of advanced disclosure, the consumers remain unaware of the second-period product's quality. When advanced disclosure occurs, the disclosed information is assumed to be entirely truthful, providing consumers with accurate knowledge of the product's quality for the upcoming period. To simplify the model, we treat the disclosure decision as a binary choice, considering only two possibilities: Disclosure or non-disclosure. In the model, H and L denote upgrade and non-upgrade decisions, respectively, while D and N denote disclosure and non-disclosure decisions, respectively. Additionally, disclosing the product's quality incurs a disclosure cost. The consumers' decision-making process involves purchasing immediately or postponing to the next period. Following the rational expectations principle, consumers form their beliefs about the future product's quality by rationally anticipating the supplier's and retailer's potential strategies, and the retailer, in turn, considers these expectations when making their disclosure decision.

Table 2. Parameter and symbol descriptions.

Parameter	Symbol description
a	Market size ($a = 1$)
p_t	Selling price of the product
w_t	Wholesale price of the product
β	Consumers' preference for product quality
δ	Discount factor in the second period
m_L	Pre-upgrade product quality
m_H	Post-upgrade product quality
k	The level of AI investment
η	The quality improvement factor brought by AI technology
μ	Consumers' prior uncertainty
τ_0	The baseline trust probability without AI support
α	The marginal trust enhancement coefficient
$\tau(k)$	The AI-driven enhancement of information disclosure's credibility
t	AI technology investment coefficient
c_k	Cost of quality upgrade with AI technology
γ	Consumers' degree of uncertainty regarding the quality upgrade
λ	Coefficient of utility reduction for low-quality products
c	Quality disclosure cost
π_m^{jk}	The profit of the supplier ($j = H, L; k = N, D$)
π_r^{jk}	The profit of the retailer ($j = H, L; k = N, D$)

Notes: Superscript H, L indicates whether the supplier upgrades the product's quality. Superscript N, D indicates whether quality information is disclosed. Subscript 1, 2 represents the first or second period.

In the competitive market, the supplier and the retailer face multiple strategic choices, particularly regarding product upgrades and quality information disclosure. Therefore, we consider four scenarios in the supply chain.

Scenario LN. The supplier chooses to offer the same quality product in two periods and does not disclose any information about the future product's quality to consumers. Consumers in the first period make purchasing decisions based on their prior beliefs about the product's quality in the second period. If the expected utility is sufficiently high, they may purchase the low-quality product in the first period. Otherwise, they may choose to wait. In the second period, the delayed consumers decide whether to purchase according to the new information.

Scenario LD. The supplier does not upgrade the product's quality but discloses the quality information in the second period. Consumers in the first period are informed about the quality of the second-period product, which influences their purchasing decisions.

Scenario HN. The supplier upgrades the product's quality in the second period but does not disclose this information to consumers. Consumers in the first period remain uncertain about the second-period quality and make decisions according to their prior beliefs.

Scenario HD. The supplier upgrades the product's quality in the second period and discloses this information to consumers. Consumers in the first period are informed about the upgraded quality, which significantly impacts their purchasing behavior. The four scenarios are shown in Figure 1.

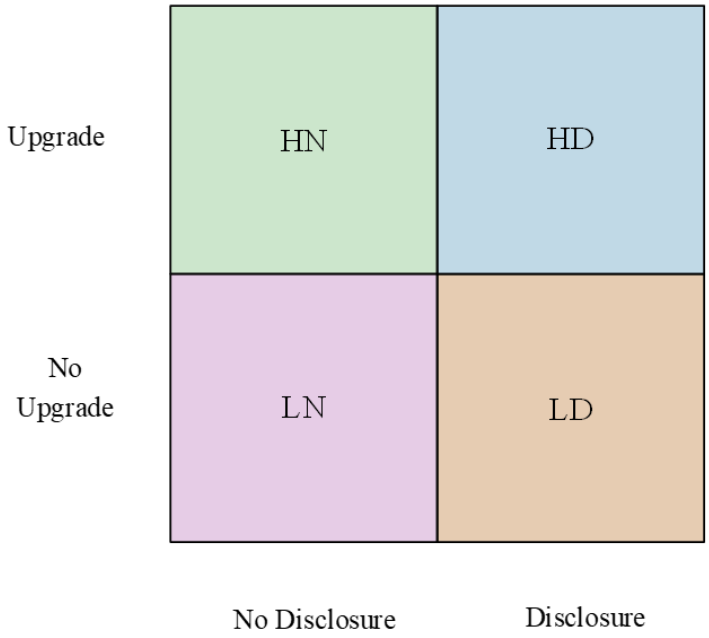


Figure 1. Four scenarios in this paper.

4. The Model

This section develops four scenarios to analyze the interplay of product upgrades enabled by AI technology, quality disclosure facilitated by AI, and consumer behavior within a two-period supply chain. The benchmark scenario (LN) establishes a baseline by examining supply chain operations in the absence of both quality upgrades and information disclosure. The remaining scenarios then explore various combinations of quality upgrades and information disclosure. For each scenario, we derive consumer utility thresholds and demand functions, incorporating the distinctive characteristics of AI-driven product improvements, including their impact on perceived quality enhancement and the management of consumers' expectations. Our analysis specifically investigates how quality disclosure policies and quality upgrade decisions, both leveraging AI technology, influence intertemporal purchasing behavior, with a particular focus on strategic waiting driven by expected AI-driven improvements. Furthermore, we evaluate how these strategies affect the distribution of profit across the supply chain and the coordination between suppliers implementing quality upgrades and retailers adopting quality information disclosure. By integrating AI technology into our model, we offer novel insights into optimal decision-making in supply chains, where AI simultaneously enables quality innovation and transforms information transparency. This research establishes a theoretical framework for formulating adaptive strategies that leverage AI technology within the supply chain, providing empirical guidance for enterprises implementing AI-driven quality upgrades and quality information disclosure. The model particularly highlights how optimal decision-making can enhance supply chains' performance in markets characterized by rapid technological evolution and heightened consumer sensitivity to quality improvements.

4.1. Scenario LN

For the benchmark model, the supplier chooses not to upgrade products in the second period. In the first period, the consumers' preference for product quality is β. The consumers' utility of buying the product is $U_1 = v + \beta m_L - p_1$, where v represents the consumers' perceived utility, m_L is the low-quality product, and p_1 is the selling price in the first period. If the supplier does not plan to upgrade the product in the second period, consumers hold a prior belief about the second-period product's quality at the beginning of the first period, denoted $\overline{m} = 1/2m_H + 1/2m_L$.

In the second period, the consumers' discount factor in the second period is $\delta \in (0, 1)$, the consumers' degree of uncertainty regarding quality upgrade is γ. The use of this parameter is consistent with previous studies like those of Liu et al. [31] and Ni et al. [32], who employed similar constructs to analyze how information asymmetry and uncertainty in quality upgrades affect consumers' decision-making in supply chain contexts. Therefore, the expected utility for consumers in the second period is $\overline{U}_2 = \delta(1 - \gamma)(v + \beta\overline{m}) - p_2$, where p_2 represents the expected selling price in the second period. Consumers decide to purchase the low-quality product in the first period if $U_1 \geq \max\left\{\overline{U}_2, 0\right\}$; otherwise, they delay their purchase. In the second period, those who delayed buying stay in the market and decide whether to buy the low-quality product. The consumers' utility of buying the low-quality product in the second period is $U_2 = \delta(v + \beta m_L) - p_2$. If $U_2 \geq 0$, consumers will purchase the product.

When the supplier does not upgrade the product and does not disclose the quality information, the demand functions for the first and second periods are derived as follows. In the first period, consumers will purchase the product if $U_1 \geq \max\left\{\overline{U}_2, 0\right\}$. Thus, the first period's demand function is

$$D_1 = 1 - \frac{\delta(1 - \gamma)\beta\overline{m} - \beta m_L + p_1 - p_2}{1 - \delta(1 - \gamma)}. \tag{4.1}$$

In the second period, consumers who delayed buying decide to buy the product in the second period if $U_2 \geq 0$. Thus, the second-period demand function is

$$D_2 = \frac{\delta(1-\gamma)\beta\overline{m} - \beta m_L + p_1 - p_2}{1-\delta(1-\gamma)} - \frac{p_2 - \delta\beta m_L}{\delta}. \tag{4.2}$$

In this scenario, the supplier chooses not to upgrade the product and does not disclose the quality information. The profit functions for the supplier and retailer are as follows:

$$\pi_m = w_1 D_1 + w_2 D_2 \tag{4.3}$$

$$\pi_r = (p_1 - w_1) D_1 + (p_2 - w_2) D_2. \tag{4.4}$$

The decision sequence in the benchmark scenario is as follows. First, the supplier sets the wholesale price w_1 to maximize the total profit across both periods. The retailer subsequently sets the selling price p_1 to optimize the total profit. Consumers decide whether to purchase in the first period or delay their purchase on the basis of their beliefs about the product quality in the second period. Second, the supplier sets the wholesale price w_2 to maximize their second-period profit. The retailer sets the selling price p_2 to maximize the second-period profit. Consumers decide whether to purchase the low-quality product in the second period. This sequential game structure, illustrated in Figure 2, is solved through backward induction to derive the equilibrium solutions. The methodology ensures optimal decision-making at each stage while accounting for forward-looking consumers' behavior and intertemporal profit considerations.

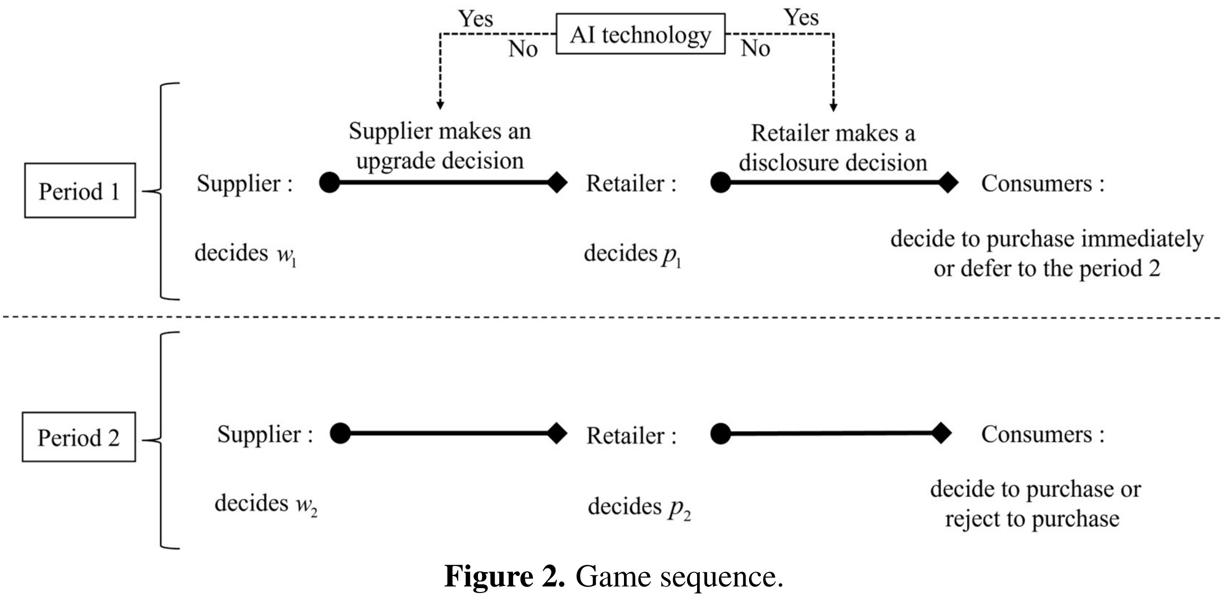


Figure 2. Game sequence.

With backward induction, the optimal solution for Scenario LN is illustrated in Table 3 below. Given the algebraic complexity of the closed-form equilibrium expressions, we introduce intermediate variables $\chi_1, b_1, M_1 \ldots\ldots$ to concisely present the results. These variables are fully defined and expressed in terms of the fundamental model parameters in Appendix A. The detailed proof process is provided in Appendix A.

Table 3. The equilibrium solution under Scenario LN.

LN	
w_1	$\dfrac{\frac{1}{2}m_L\beta\left(512+\chi_3+\chi_4\delta^3+\chi_5\delta^4+k\chi_1\chi_5\right)+\chi_9+\chi_6\delta^2+\chi_7\delta^3+\chi_8\delta^4}{4\chi_2^2\chi_{31}}$
w_2	$\dfrac{\left(4\left(1+\chi_1\delta\right)\chi_{10}+m_L\beta\left(96+\delta\left(\chi_{14}+\chi_1\chi_{15}\delta^2-k\chi_1\chi_2^2\right)\right)\right)}{8(1+\gamma\delta)\chi_2\chi_{31}}$
p_1	$\dfrac{4\,(1+\chi_1\delta)\chi_{10}+m_L\beta\,(96+\delta\,(\chi_{11}+\chi_1\,(\chi_{12}+k\chi_1\chi_2\chi_{13}))}{4\chi_2\chi_{31}}$
p_2	$\dfrac{3\delta\left(4\left(1+\chi_1\delta\right)\chi_{10}+m_L\beta\left(96+\delta\left(\chi_{14}+\chi_1\chi_{15}\delta^2-k\chi_1\chi_2^2\right)\right)\right)}{16(1+\gamma\delta)\chi_2\chi_{31}}$
D_1	$\dfrac{4\,(1+\chi_1\delta)\chi_{16}+m_L\beta\left(32+\delta\left(-52+80\gamma+4\chi_{18}\delta+\chi_{17}\delta^2+k\chi_1\chi_2^2\right)\right)}{16\,(1+\chi_1\delta)\,(1+\gamma\delta)\chi_{31}}$
D_2	$\dfrac{4\,(1+\chi_1\delta)\chi_{10}+m_L\beta\left(96+\delta\left(\chi_{14}+\chi_1\chi_{15}\delta^2-k\chi_1\chi_2^2\right)\right)}{16\,(1+\chi_1\delta)\,\chi_2\chi_{31}}$
π_r	$\dfrac{\delta\chi^2+2\chi_{31}\,(\chi+m_L\beta\chi_{35}\,(4\,(1+\chi_1\delta)\,\chi+m_L\beta\,(32+\delta\chi_2))}{256\,(1+\chi_1\delta)\,(1+\gamma\delta)^2\chi_2{\chi_{31}}^2}$
π_m	$\dfrac{\delta{\chi_{40}}^2+2\,[\chi_{30}+m_L\beta\left(32+\delta\left(\chi_{33}+k\chi_1{\chi_2}^2\right)\right))\left(\frac{1}{2}m_L\beta\chi_{36}+\chi_{37}\right)}{128\,(1+\chi_1\delta)\,(1+\gamma\delta){\chi_2}^2{\chi_{31}}^2}$

4.2. *Scenario LD*

In scenario LD, while the supplier implements the quality upgrades without AI technology in the second period, the retailer utilizes the quality disclosure systems to reveal the future product's quality information during the first period. Consumers are informed about the product's quality in the second period, which influences their buying decisions. Firstly, consumers' utility of buying the product in the first period is $U_1 = v + \beta m_L - p_1$. Since the retailer discloses the second-period quality, consumers know that the product's quality is $\overline{m} = m_L$. The expected utility for consumers in the second period is $\overline{U}_2 = \lambda\delta\,(v + \beta m_L) - p_2$, where p_2 is the selling price in the second period. Consumers decide to purchase in the first period if $U_1 \geq \max\left\{\overline{U}_2, 0\right\}$. Otherwise, they delay their purchase. At the beginning of the second period, those who delayed buying stay in the market and decide whether to buy the low-quality product. The consumers' utility of buying the low-quality product in the second period is $U_2 = \lambda\delta\,(v + \beta m_L) - p_2$. Consumers will purchase in the second period if $U_2 \geq 0$.

Consumers purchase in the first period if $U_1 \geq \max\left\{\overline{U}_2, 0\right\}$. Thus, the first period's demand function is

$$D_1 = 1 - \frac{\lambda\delta\beta_L - \beta m_L + p_1 - p_2}{1 - \lambda\delta}. \tag{4.5}$$

Consumers who delay their purchase decide to buy in the second period if $U_2 \geq 0$. Thus, the second period's demand function is

$$D_2 = \frac{\lambda\delta\beta_L - \beta_L + p_1 - p_2}{1 - \lambda\delta} - \frac{p_2 - \lambda\delta\beta m_L}{\lambda\delta}. \tag{4.6}$$

The supplier's profit is

$$\pi_m = w_1 D_1 + w_2 D_2. \tag{4.7}$$

The retailer's profit is

$$\pi_r = (p_1 - w_1)\, D_1 - c + (p_2 - w_2)\, D_2. \tag{4.8}$$

With backward induction, the optimal solution for Scenario LD is illustrated in Table 4 below.

Table 4. The equilibrium solution under Scenario LD.

LD	
w_1	$\dfrac{(1+m_L\beta)\,(\delta\lambda-1)(128+\delta\lambda(79\delta\lambda-200))}{2(4-3\delta\lambda)^2(7\delta\lambda-8)}$
w_2	$\dfrac{(1+m_L\beta)\,\delta\lambda(\delta\lambda-1)(19\delta\lambda-24)}{2(3\delta\lambda-4)(7\delta\lambda-8)}$
p_1	$\dfrac{(1+m_L\beta)\,(\delta\lambda-1)(19\delta\lambda-24)}{(3\delta\lambda-4)(7\delta\lambda-8)}$
p_2	$\dfrac{3\,(1+m_L\beta)\,\delta\lambda(\delta\lambda-1)(19\delta\lambda-24)}{4(3\delta\lambda-4)(7\delta\lambda-8)}$
D_1	$1-\dfrac{-m_L\beta+m_L\beta\delta\lambda+\chi_{42}-\chi_{43}}{1-\delta\lambda}$
D_2	$\dfrac{-m_L\beta+m_L\beta\delta\lambda+\chi_{42}-\chi_{43}}{1-\delta\lambda}-\dfrac{-m_L\beta\delta\lambda+\chi_{43}}{\delta\lambda}$
π_r	$\dfrac{(1+m_L\beta)^2\,(\delta\lambda-1)(\delta\lambda(2112+\delta\lambda(269\delta\lambda-1376))-1024)}{16(8-7\delta\lambda)^2(4-3\delta\lambda)^2}-c$
π_m	$\dfrac{(1+m_L\beta)^2\,(8-5\delta\lambda)^2(\delta\lambda-1)}{4(4-3\delta\lambda)^2(7\delta\lambda-8)}$

4.3. Scenario HN

In Scenario HN, the supplier implements the quality upgrades with AI technology in the second period, but the retailer does not disclose the quality information. Consumers remain uncertain about the second-period quality and make decisions based on their prior beliefs. The consumers' utility of buying the product in the first period is $U_1 = v + \beta m_L - p_1$. Consumers then have a prior belief about the quality in the second period. The expected utility in the second period is $\overline{U}_2 = \delta(1-\gamma)(v+\beta\overline{m}) - p_2$. Consumers decide to purchase in the first period if $U_1 \geq \max\left\{\overline{U}_2, 0\right\}$; otherwise, they delay their purchase. In the second period, those who delayed buying decide whether to purchase the upgraded product according to the realized quality. The consumers' utility of buying the low-quality product in the second period is $U_2 = \delta\,(v + \beta m_H) - p_2$.

The consumers will purchase in the first period if $U_1 \geq \max\left\{\overline{U}_2, 0\right\}$. Thus, the first period's demand function is

$$D_1 = 1 - \frac{\delta(1-\gamma)\beta\overline{m} - \beta m_L + p_1 - p_2}{1-\delta(1-\gamma)}. \tag{4.9}$$

The consumers who delay their purchase decide to buy in the second period if $U_2 \geq 0$. Thus, the second period's demand function is

$$D_2 = \frac{\delta(1-\gamma)\beta\overline{m} - \beta_L + p_1 - p_2}{1-\delta(1-\gamma)} - \frac{p_2 - \delta\beta m_H}{\delta}. \tag{4.10}$$

The supplier's profit is

$$\pi_m = w_1 D_1 + \left(w_2 - \frac{1}{2}tk^2\right) D_2. \tag{4.11}$$

The retailer's profit is

$$\pi_r = (p_1 - w_1)\, D_1 + (p_2 - w_2)\, D_2. \tag{4.12}$$

With backward induction, the optimal solution for Scenario HN is illustrated in Table 5 below.

Table 5. The equilibrium solution under Scenario HN.

HN	
w_1	$\frac{256 - 656\delta + \chi_{41} + \delta\left(\chi_{45} + 2\delta\chi_{44} + km_L\beta\chi_{46}\right)}{4\chi_2^2\chi_{31}}$
w_2	$\frac{tk^2(1+\gamma\delta)\chi_{48} + \delta\left(4\left(1+\chi_1\delta\right)\chi_{10} + m_L\beta\left(-\left(\left(2+\chi_1\delta\right)\chi_2{}^2\right) + k\chi_{47}\right)\right)}{8(1+\gamma\delta)\chi_2\chi_{31}}$
p_1	$\frac{4\chi_{51} + tk^2(1+\gamma\delta)(6+(6\gamma-5)\delta) + m_L\beta\chi_{50}}{4\chi_2\chi_{31}}$
p_2	$\frac{tk^2\chi_{52} + 3\delta\left(4\chi_{51} + m_L\beta\left(k\chi_{47} - \left(\left(2+\chi_1\delta\right)\chi_2{}^2\right)\right)\right)}{16(1+\gamma\delta)\chi_2\chi_{31}}$
D_1	$\frac{\chi_{30} + tk^2(1+\gamma\delta)(10+(10\gamma-9)\delta) + m_L\beta\chi_{54}}{16\left(1+\chi_1\delta\right)\left(1+\gamma\delta\right)\chi_{31}}$
D_2	$\frac{-tk^2(1+\gamma\delta)\chi_{55} + \delta\left(4\chi_{51} + m_L\beta\left(k\chi_{47} - \left(\left(2+\chi_1\delta\right)\chi_2{}^2\right)\right)\right)}{16\delta\left(1+\chi_1\delta\right)\chi_2\chi_{31}}$
π_r	$\frac{2\delta\chi_{31}\left(4\left(1+\chi_1\delta\right)\chi_{28} + tk^2\chi_{71} + m_L\beta\chi_{70}\right) + \chi_{73}{}^2}{256\delta\left(1+\chi_1\delta\right)\left(1+\gamma\delta\right)\chi_2{}^2\chi_{31}}$
π_m	$\frac{2\delta\chi_{78}\chi_{79} + \Big(tk^2\chi_{76} + \delta\chi_{75}\Big)\Big)\Big(tk^2\chi_{76} + \delta\chi_{77}\Big)}{128\delta\left(1+\chi_1\delta\right)\left(1+\gamma\delta\right)\chi_2{}^2\chi_{31}{}^2}$

4.4. Scenario HD

In Scenario HD, the supplier implements the quality upgrades with AI technology in the second period, and the retailer discloses the quality information at the beginning of the first period. Consumers are informed about the upgraded quality, which influences their purchasing decisions. First, the consumers' utility of buying the product in the first period is $U_1 = v + \beta m_L - p_1$. Consumers know the quality in the second period is m_H. The utility in the second period is $U_2 = \delta\,(v + \beta m_H) - p_2$. Consumers decide to purchase in the first period if $U_1 \geq \max\{U_2, 0\}$; otherwise, they delay their purchase. In the second period, those consumers who delayed buying decide whether to purchase the upgraded product.

The consumers will purchase in the first period if $U_1 \geq \max\{U_2, 0\}$. Thus, the first period's demand function is

$$D_1 = 1 - \frac{\delta\beta_H - \beta m_L + p_1 - p_2}{1-\delta}. \tag{4.13}$$

The consumers who delay their purchase decide to buy in the second period if $U_2 \geq 0$. Thus, the second period's demand function is

$$D_2 = \frac{\delta\beta m_H - \beta m_L + p_1 - p_2}{1-\delta} - \frac{p_2 - \delta\beta m_H}{\delta}. \tag{4.14}$$

The supplier's profit is

$$\pi_m = w_1 D_1 + \left(w_2 - \frac{1}{2}tk^2\right) D_2. \tag{4.15}$$

The retailer's profit is

$$\pi_r = (p_1 - w_1)\, D_1 - c + (p_2 - w_2)\, D_2. \tag{4.16}$$

With backward induction, the optimal solution for Scenario HD is illustrated in Table 6 below.

Table 6. The equilibrium solution under Scenario HD.

HD	
w_1	$\dfrac{-256 + m_L\beta\chi_{19} + \frac{1}{2}tk^2\chi_{20} + \delta\left(\chi_{21} + km_L\beta\chi_{22}\right)}{4(4-3\delta)^2(7\delta-8)}$
w_2	$\dfrac{1}{2}\left(\dfrac{1}{2}tk^2 + (k-1)m_L\beta\delta + \dfrac{\delta\left(\chi_{23} + \frac{1}{2}tk^2(6-5\delta) + m_L\beta\chi_{24}\right)}{2(3\delta-4)(7\delta-8)}\right)$
p_1	$\dfrac{\chi_{23} + \frac{1}{2}tk^2(6-5\delta) + m_L\beta\chi_{24}}{2(3\delta-4)(7\delta-8)}$
p_2	$\dfrac{\frac{1}{2}tk^2\chi_{25} + 3\delta\left(\chi_{23} + m_L\beta\left(k(64+\delta(47\delta-110)) - (4-3\delta)^2\right)\right)}{8(3\delta-4)(7\delta-8)}$
D_1	$\dfrac{2\left(8 + \frac{5}{2}tk^2 + 8m_L\beta\right) - \left(34 + \frac{9}{2}tk^2 + 2(12+5k)m_L\beta\right)\delta + 9\chi_{26}\delta^2}{8(\delta-1)(7\delta-8)}$
D_2	$\dfrac{1}{16}\left(\dfrac{4 - \frac{3}{2}tk^2 + 4km_L\beta}{4-3\delta} + \dfrac{2\left(\frac{1}{2}tk^2 - (k-1)m_L\beta\right)}{\delta-1} - \dfrac{2tk^2}{\delta} + \dfrac{\frac{7}{2}tk^2 - 8\chi_{26}}{7\delta-8}\right)$
π_r	$\dfrac{\frac{1}{2}t^2k^4\chi_{60} + tk^2\delta\chi_{57} + \delta\left(\chi_{61} - 4m_L\beta\chi_{62} + m_L^2\beta^2\chi_{59}\right)}{64(8-7\delta)^2(4-3\delta)^2(\delta-1)\delta}$
π_m	$\dfrac{\frac{1}{2}t^2k^4\chi_{65} + tk^2\delta\chi_{66} + \delta\left(4(8-5\delta)^2(-1+\delta)^2 - 4m_L\beta\chi_{63} + m_L^2\beta^2\chi_{64}\right)}{16(4-3\delta)^2(7\delta-8)(\delta-1)\delta}$

5. Analysis

This section analyzes the interplay between quality upgrade decisions and disclosure strategies in a supply chain. Specifically, we first examine how varying quality upgrade levels facilitated by AI technology impact suppliers' quality upgrade decisions, assuming that the retailers' disclosure strategies remain constant. Subsequently, we investigate how consumers' quality preferences and the degree of uncertainty influence retailers' disclosure choices, given that suppliers' AI-driven upgrade strategies are predetermined.

Proposition 5.1. (i) $w_1^{HN} > w_1^{LN} > w_1^{LD} > w_1^{HD}$.
(ii) $k < k_1, w_2^{HN} > w_2^{HD} > w_2^{LN} > w_2^{LD}, k > k_1, w_2^{HN} > w_2^{HD} > w_2^{LD} > w_2^{LN}$.
(iii) $p_1^{HN} > p_1^{HD}, p_1^{LN} > p_1^{LD}, p_2^{HN} > p_2^{HD} > p_2^{LD} > p_2^{LN}$.

Proof. See Appendix B.

Proposition 5.1 (i) indicates that the wholesale price is highest when the supplier upgrades the product but does not disclose the quality information (HN) in the first period. This occurs because the consumers remain uncertain about future upgrades, reducing their incentive to delay purchases. Conversely, the wholesale price is lowest under the upgrade-and-disclosure strategy (HD), as early disclosure intensifies the consumers' strategic waiting behavior, forcing the supplier to lower prices to stimulate demand. Non-upgraded products follow a similar logic, with non-disclosure (LN) maintaining higher prices than disclosure (LD) due to reduced consumer hesitation. In the second period, when the upgrade level with AI technology is low ($k < k_1$), the wholesale price under the upgrade-without-disclosure strategy (HN) remains the highest, as consumers perceive higher value in the upgraded product but lack full information. However, when the upgrade level with AI technology is high ($k > k_1$), non-upgraded products under non-disclosure (LN) see the sharpest price decline, as consumers strongly prefer waiting for significantly improved versions. In terms of the selling price, similar dynamics apply. In the first period, the selling price for the upgraded, non-disclosed product (HN) is the highest, followed by the non-upgraded product without disclosure (LN), then the upgraded product with disclosure (LD), and, finally, the non-upgraded product with disclosure (HD). This hierarchy occurs because the consumers are more likely to delay their purchase in response to disclosures of the future product's quality, resulting in a lower selling price to stimulate immediate demand. In the second period, when the upgrade level is low ($k < k_1$), the selling price for the upgraded, non-disclosed product (HN) is still the highest, followed by the upgraded product with disclosure (HD), the non-upgraded product without disclosure (LN), and the non-upgraded product with disclosure (LD). When the upgrade level is high ($k > k_1$), the selling price for non-upgraded products under non-disclosure (LN) drops sharply, as the consumers prefer waiting for the significantly improved version. Then firms should carefully balance their upgrade and disclosure strategies based on the intensity of AI innovation. For example, smartphone manufacturers like Apple may withhold details about minor hardware upgrades to sustain premium pricing, although disclosing major AI-driven features early can help manage consumers' expectations and optimize intertemporal demand. For the proof, see Appendix B.

Corollary 5.1. (i) $\frac{\partial w_1^{LN}}{\partial k} < 0, \frac{\partial w_1^{LD}}{\partial k} = 0, \frac{\partial w_1^{HN}}{\partial k} > 0, \frac{\partial w_1^{HD}}{\partial k} < 0$.
(ii) $\frac{\partial w_2^{LN}}{\partial k} > 0, \frac{\partial w_2^{LD}}{\partial k} = 0, \frac{\partial w_2^{HN}}{\partial k} > 0, \frac{\partial w_2^{HD}}{\partial k} > 0$.

Proof. See Appendix B.

Corollary 5.1(i) shows that the first-period wholesale price under the no-upgrade and non-disclosure strategy (LN) decreases when the upgrade level with AI technology (k) is high, while the wholesale price under the upgrade-without-disclosure strategy (HN) increases with k, and the wholesale price under the upgrade-with-disclosure strategy (HD) decreases with k. This pattern arises because higher k values under LN lead consumers to anticipate future upgrades, thereby lowering their willingness to pay for the current products. This anticipation forces price reductions to stimulate demand. In contrast, under HN, greater k values enhance the perceived value of the upgrades, allowing price increases despite consumer uncertainty. However, the HD strategy exhibits a price decline because the early disclosure of substantial upgrades intensifies consumers' waiting behavior. Turning to the second period, we observe from Corollary 5.1(ii) that the wholesale price under the no-upgrade and nondisclosure strategy (LN) decreases with k, whereas the wholesale prices under both upgrade strategies (HN and HD) increase with k. In the second period, non-upgraded products (LN) become less attractive as k increases, necessitating price cuts, while upgraded products (HN/HD) command premium pricing due to their enhanced value, with disclosed upgrades (HD) benefiting from stronger consumer confidence. These findings suggest that firms should adopt differentiated pricing strategies depending on their AI upgrade plans and disclosure policies. For example, consumer electronics manufacturers introducing incremental AI improvements may benefit from nondisclosure to maintain prices, whereas those launching breakthrough AI features (high k) should combine upgrades with strategic disclosure to optimize intertemporal pricing and demand.

Proposition 5.2. (i) If $k < k_2$, then $\pi_m^{HN} > \pi_m^{LN}$. If $k \geq k_2$, then $\pi_m^{HN} \leq \pi_m^{LN}$.

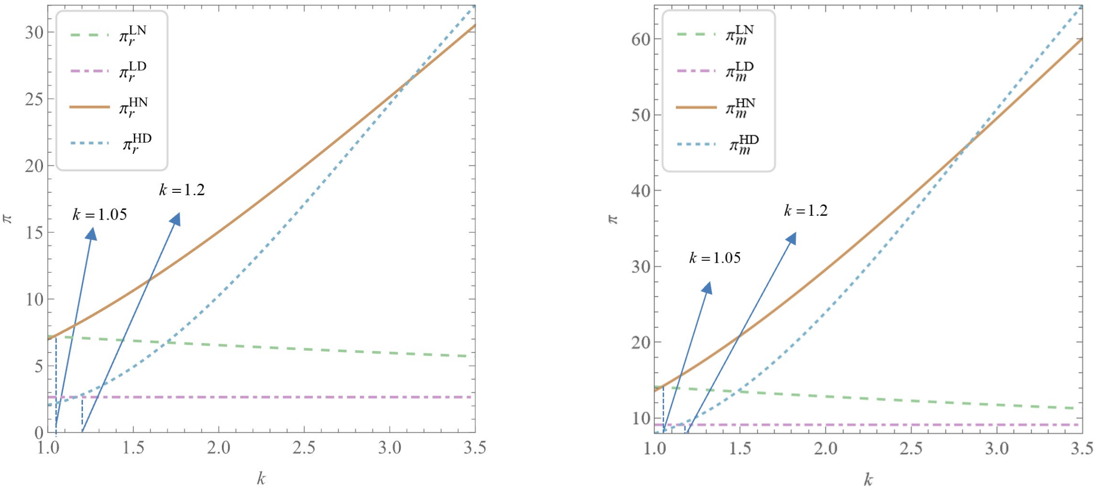
(ii) If $k < k_3$, then $\pi_m^{LD} > \pi_m^{HD}$. If $k \geq k_3$, then $\pi_m^{LD} \leq \pi_m^{HD}$.

Proof. See Appendix B

The equilibrium profit expressions in Appendix B indicate that the supplier's profitability arises from the trade-off between the marginal benefits of AI-driven upgrades and the associated costs, which are jointly determined by the upgrade level and the AI investment cost coefficient. From Proposition 5.2, we can know that for any given cost coefficient, when the AI-driven upgrade level is below the threshold that k_2 ($k_2 = 1.05$), the supplier's profit under the upgrade-without-disclosure strategy (HN) is lower than under the no-upgrade strategy (LN); however, when k exceeds k_2 ($k_2 = 1.05$), this relationship reverses. Similarly, when k is below the threshold k_3 ($k_3 = 1.2$), the supplier's profit under the no-upgrade-with-disclosure strategy (LD) exceeds that under the upgrade-with-disclosure strategy (HD), but when k surpasses k_3 ($k_3 = 1.2$), the HD strategy becomes more profitable. This pattern emerges because at lower k levels, the cost of achieving the upgrade outweigh the benefits of quality improvements, making no-upgrade strategies more profitable regardless of the disclosure choices. However, as k increases beyond the critical thresholds, the enhanced product value and demand stimulation from the upgrades compensate for the associated costs.

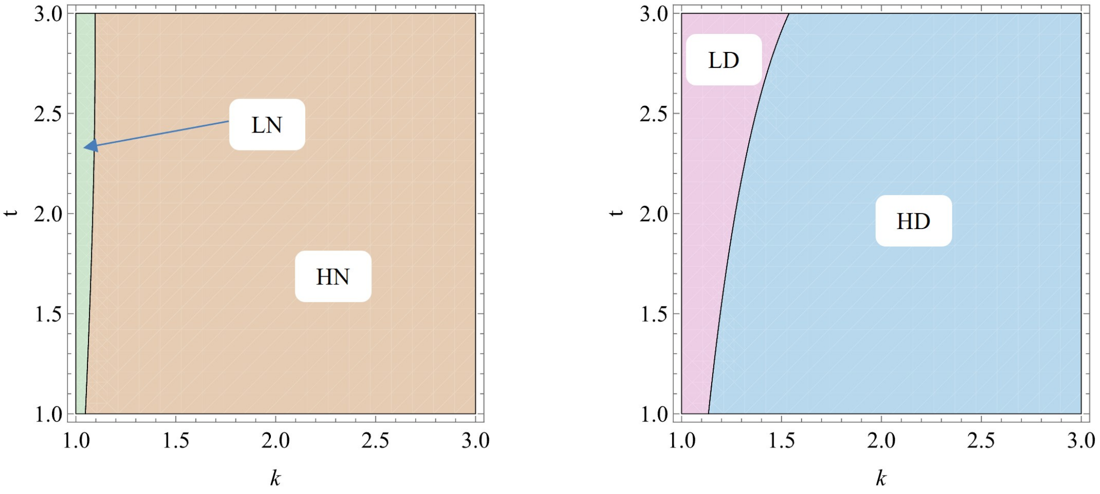
Notably, Figure 3 demonstrates that the retailers' profit trends align with the suppliers' profit trends, as both parties' earnings are fundamentally tied to the same market dynamics. Following the parameter calibration approaches adopted in Sun et al. [33] and Ni et al. [32], and taking into account the equilibrium constraints across varying degrees of information asymmetry, the parameters are specified as follows: $\beta = 0.8, \gamma = 0.7, \lambda = 0.7, \delta = 0.6, t = 1.5, m_L = 12, c = 1.5$, and $k \in [1, 3.5]$. Furthermore, Figure 4(a) reveals that when retailers choose non-disclosure, suppliers should avoid upgrades at a lower k levels, especially when the AI investment cost coefficient (t) is higher. Suppliers should pursue upgrades only when k is large enough to offset the cost associated with t. Conversely, Figure 4(b) shows that under retailer disclosure, the suppliers benefit from upgrading only when k is high and t is low, as early information disclosure magnifies both the advantages of significant upgrades and the drawbacks of costly marginal improvements.

These findings highlight the necessity of aligning AI investment decisions with both technological capability and information disclosure strategies within the supply chain. For instance, semiconductor manufacturers launching next-generation chips should disclose their upgrade information only when advanced AI features such as real-time defect prediction deliver substantial performance gains ($k > 1.2$) that are sufficient to offset the costs, whereas minor upgrades ($k < 1.05$) require restrained communication to prevent premature demand shifts. These findings emphasize that AI investment should align with technological capability and the disclosure strategy, and the single-rollover results provide a benchmark for dual-rollover settings, where the coexistence of upgraded and legacy products helps stabilize profitability by meeting diverse consumers' preferences.



(a) The impact of k on retailers' profits **(b)** The impact of k on suppliers' profits

Figure 3. The impact of k on suppliers' and retailers' profits.



(a) The retailer does not disclose information. **(b)** The retailer discloses information.

Figure 4. The impact of k and t on retailers' profits.

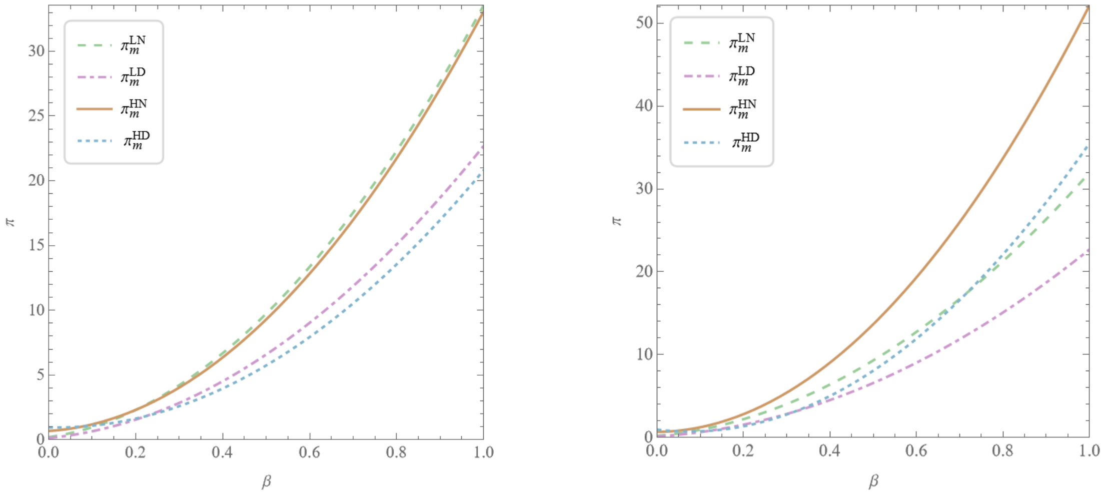
Corollary 5.2. (i) $\frac{\partial \pi_m^{LN}}{\partial \beta} > 0, \frac{\partial \pi_m^{LD}}{\partial \beta} > 0, \frac{\partial \pi_m^{HN}}{\partial \beta} > 0, \frac{\partial \pi_m^{HD}}{\partial \beta} > 0.$

(ii) $\frac{\partial \pi_m^{LN}}{\partial \delta} > 0, \frac{\partial \pi_m^{LD}}{\partial \delta} > 0, \delta < \delta_1, \frac{\partial \pi_m^{AN}}{\partial \delta} < 0, \delta > \delta_1, \frac{\partial \pi_m^{LN}}{\partial \delta} > 0, \frac{\partial \pi_m^{HD}}{\partial \delta} > 0.$

Proof. See Appendix B.

(i) For all four strategic scenarios (LN, LD, HN, and HD), the supplier's profit increases monotonically with the consumers' quality preference parameter, indicating that a stronger consumer valuation for product quality consistently enhances profitability. (ii) With respect to the discount factor, the supplier's profit exhibits distinct patterns across different strategies. Specifically, under the LN, LD, and HD scenarios, the supplier's profit increases with δ, implying that higher consumer patience toward delayed purchases enhances overall profitability. However, under the HN scenario, when $\delta < \delta_1$, the supplier's profit decreases with δ due to intensified consumer waiting behavior; conversely, when $\delta > \delta_1$, the profit increases with δ as the perceived benefits of AI-driven upgrades outweigh the negative intertemporal effects.

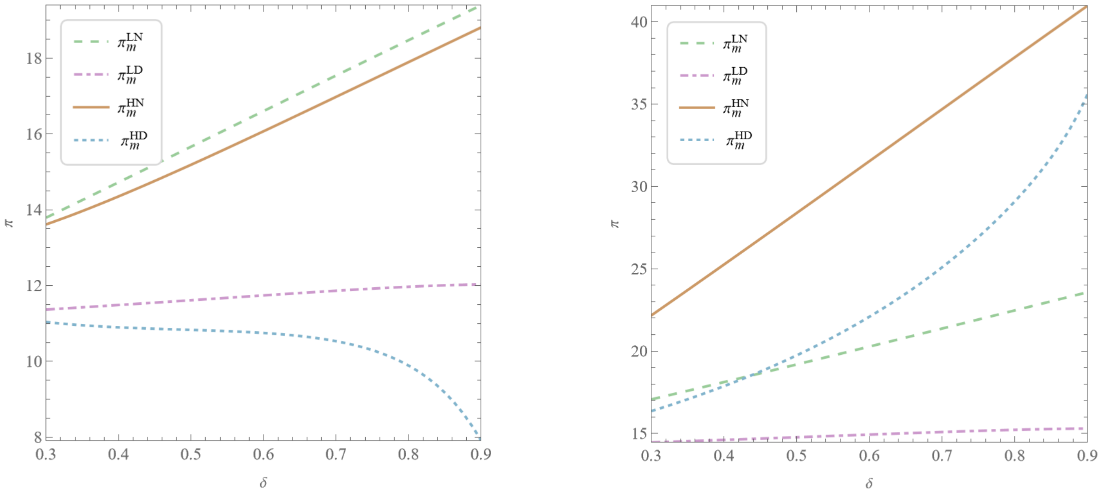
From Corollary 5.1, it can be observed that the equilibrium results are robust with respect to variations in both β and δ. As shown in Figure 5(b), when the other parameters are held constant and $k = 1.05$ or $k = 1.5$, the supplier's profit rankings under different strategies remain consistent with Proposition 5.2, confirming the monotonic relationship between β and profitability. Similarly, Figure 6(a) that for $k = 1.05$ and $k = 1.5$, the profit trends with respect to δ also conform to the theoretical predictions in Proposition 5.2. These results validate the robustness and general applicability of the model, showing that the strategic implications derived from Proposition 5.2 remain stable across varying degrees of the intensity of consumer preference and temporal discounting.



(a) $k = 1.05$

(b) $k = 1.5$

Figure 5. The impact of β on suppliers' profits.



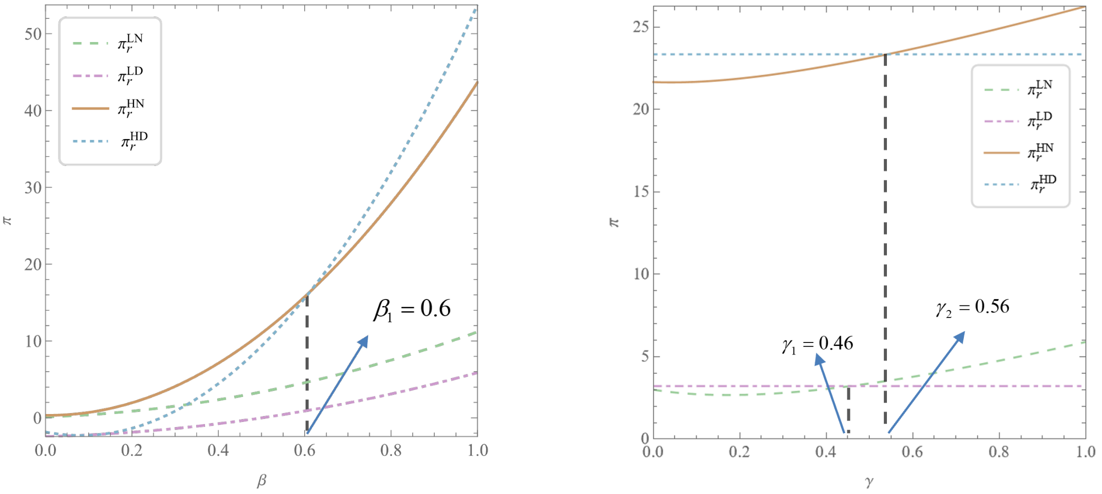
(a) $k = 1.05$ **(b)** $k = 1.5$

Figure 6. The impact of δ on suppliers' profits.

Proposition 5.3. (i) $\pi_r^{LD} \leq \pi_r^{LN}$. If $\beta < \beta_1$, then $\pi_r^{HN} > \pi_r^{HD}$. If $\beta \geq \beta_1$, then $\pi_r^{HD} \geq \pi_r^{HN}$. (ii) If $\gamma \leq \gamma_1$, then $\pi_r^{LD} \geq \pi_r^{LN}$. If $\gamma > \gamma_1$, then $\pi_r^{LN} > \pi_r^{LD}$. If $\gamma \leq \gamma_2$, then $\pi_r^{HD} \geq \pi_r^{HN}$. If $\gamma > \gamma_2$, then $\pi_r^{HN} > \pi_r^{HD}$.

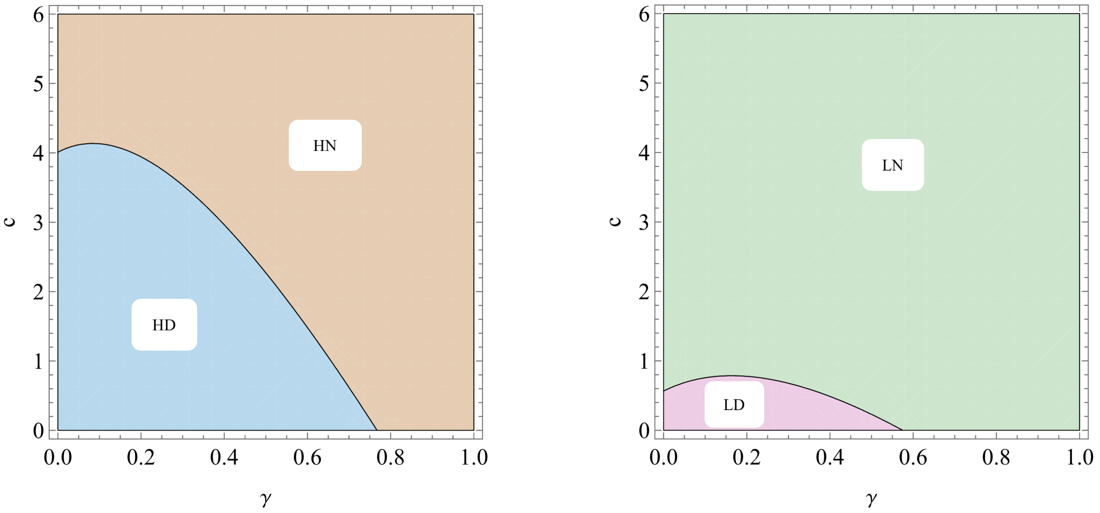
Proof. See Appendix B.

The analytical results in Appendix B indicate that the retailers' disclosure strategies depend on the interaction between market uncertainty and consumers' quality preference. Proposition 5.3(i) illustrates that when the supplier chooses not to upgrade the product's quality, the retailer achieves higher profits by adopting a nondisclosure strategy compared with disclosure. For suppliers opting to upgrade, when consumers' quality preference is below the threshold β_1 ($\beta_1 = 0.6$), nondisclosure yields greater retailer profits. However, when β exceeds β_1 ($\beta_1 = 0.6$), disclosure becomes more profitable. Proposition 5.3(ii) shows that when the supplier does not upgrade, disclosure is preferred at low uncertainty levels ($\gamma \leq \gamma_1 = 0.46$), while nondisclosure dominates at high uncertainty ($\gamma > \gamma_1 = 0.46$). Similarly, with product upgrades, disclosure is optimal when $\gamma < \gamma_2 = 0.56$, but nondisclosure prevails when $\gamma > \gamma_2 = 0.56$. This demonstrates consistent retailer disclosure preferences across suppliers' upgrade decisions as uncertainty varies. The reason is that lower uncertainty reduces consumers' hesitation, making disclosure beneficial by enhancing market transparency and demand. Conversely, higher uncertainty necessitates non-disclosure to prevent profit erosion from consumers' skepticism. As shown in Figure 7, these patterns hold regardless of the upgrade decisions. Figure 8(a) further reveals that with product upgrades, disclosure maximizes profits when both uncertainty and upgrade costs are low, while nondisclosure is preferred when these factors are high. Figure 8(b) shows similar trends for non-upgraded products, though the beneficial range for disclosure is narrower due to smaller profit margins that make disclosure less impactful. Retailers should tailor their disclosure strategies according to consumers' characteristics and the technological capabilities of supply chain partners. In practice, when market uncertainty is low, such as for mature product lines with well-established AI functions, transparent disclosure helps enhance consumer's trust and supports quality-based differentiation. By contrast, under the high uncertainty associated with new or unproven AI technologies, restrained disclosure can reduce consumers' skepticism and stabilize early demand. This adaptive disclosure approach allows retailers to balance transparency and profitability across different stages of product development and market evolution. In addition, the interaction between disclosure and AI-driven upgrades described in Proposition 5.3 also provides implications for dual-rollover scenarios. When upgraded and original products coexist, the retailers' disclosure choices influence not only the consumers' purchasing timing but also substitution between product generations.



(a) The impact of β on retailers' profits **(b)** The impact of γ on retailers' profits

Figure 7. The impact of β and γ on retailers' profits.



(a) The supplier upgrades with AI **(b)** The supplier does not upgrade with AI

Figure 8. The impact of γ and c on supplier's profits.

6. Dual-Rollover Strategy

This section extends the single-rollover analysis to examine a dual-rollover strategy employed by suppliers following product quality upgrades. This dual-rollover strategy involves the gradual phasing out of older products after innovation, resulting in the coexistence of both upgraded and non-upgraded products in the subsequent period. While this coexistence can potentially increase profits, it also introduces competition between the two product categories. Given the prevalence of dual-rollover strategies in real-world scenarios, this section analyzes this situation and compares it with the single-rollover case.

6.1. Scenario HND

In this scenario, the supplier implements product quality upgrades in the second period while maintaining the original product line, yet elects not to disclose this strategic information to the consumers. During the first period, the consumers remain unaware of the forthcoming product enhancements and base their purchasing decisions solely on the existing product information and market expectations. The consumers' expectation on the quality of the products in the second period is $E[m] = 1/2m_H + 1/2m_{\iota}$. The consumers' utility of buying products in the second period is $\overline{U_2} = \delta(1-\gamma)(v+\beta m) - 1/2p_{2H} - 1/2p_{2L}$. In the first period, the consumers' utility is $U_1 = v + \beta m_L - p_1$. If $U_1 \geq \max\left\{\overline{U}_2, 0\right\}$, the consumers decide to purchase. Otherwise, they delay their purchase. In the second period, $U_{2H} = \delta\left(v + \beta m_H\right) - P_{2H}.U_{2L} = \lambda\delta\left(v + \beta m_L\right) - P_{2L}$. If $U_{2H} \geq \max\left\{U_{2L}, 0\right\}$, the consumers will purchase the upgraded product. If $U_{2L} \geq \max\left\{U_{2H}, 0\right\}$, they will purchase the non-upgraded product; otherwise, they will not purchase.

The demand function in the first period is

$$D_1 = 1 - \frac{\delta(1-\gamma)\beta m - p_{2H}/2 - p_{2L}/2 + p_1}{1 - \delta(1-\gamma)}. \tag{6.1}$$

The demand function in the second period is

$$D_{2H} = \frac{\delta(1-\gamma)\beta m - p_{2H}/2 - p_{2L}/2 + p_1}{1 - \delta(1-\gamma)} - \frac{\lambda\delta\beta m_L - \delta\beta m_H + p_{2H} - p_{2L}}{\delta(1-\lambda)} \tag{6.2}$$

$$D_{2L} = \frac{\lambda\delta\beta m_L - \delta\beta m_H + p_{2H} - p_{2L}}{\delta(1-\lambda)} - \frac{p_{2L} - \lambda\delta\beta m_L}{\lambda\delta}. \tag{6.3}$$

In this scenario, the supplier chooses not to upgrade the product and does not disclose the quality information. The profit functions of the supplier and retailer are as follows:

$$\pi_m = w_1 D_1 + \left(w_{2H} - \frac{1}{2}tk^2\right) D_{2H} + w_{2L} D_{2L} \tag{6.4}$$

$$\pi_r = \left(p_1 - w_1\right) D_1 + \left(p_{2H} - w_{2H}\right) D_{2H} + \left(p_{2L} - w_{2L}\right) D_{2L} \tag{6.5}$$

With backward induction, the optimal solution for Scenario HND is illustrated in Table 7 below.

Table 7. The equilibrium solution under Scenario HND.

HND	
w_1	$\frac{b_{11}64(1+\delta(-1+\lambda))^3}{4b_{14}(4-3\delta)(20+\delta(-20+7\lambda)+2\delta(1-\lambda))^2}$
w_{2H}	$\frac{32(1+\delta(-1+\lambda))^2 96\left(m_L\beta(-2+\delta)+2(-1+\delta)\right)(-1+\delta)^2}{8(8+\delta(-8+\lambda))(1+\delta(-1+\lambda))}$
w_{2L}	$\frac{tk^2+tk^2\delta(-1+\lambda)+\delta\lambda\left(b_2+m_L\beta b_3\right)}{2(2+2\delta(-1+\lambda)+\delta(1-\lambda))}$
p_1	$\frac{\delta\lambda\left(b_2+m_L\beta\delta(\lambda-1)\right)-2\bigl(tk^2+4(-8+\delta(8+\lambda))+m_L\beta\left(4+\delta b_8\right)}{2(2+2\delta(-1+\lambda)+\delta(1-\lambda))}$
p_{2H}	$\frac{256(-1+\delta)(1+\delta(-1+\lambda))^3-2(-12+\delta(12+\lambda))}{8(8+\delta(-8+\lambda))(1+\delta(-1+\lambda))}$
p_{2L}	$\frac{3\delta\lambda\delta(1-\lambda)^5-2\left(tk^2+4b_{14}+mL\beta(4+\delta(-2-2k+\lambda))\right)\delta(1-\lambda)^6\bigr)}{8(4+\delta(-4+\lambda))(1+\delta(-1+\lambda)}$
D_1	$\frac{32(1+\delta(-1+\lambda))^2 b_9+2(1+\delta(-1+\lambda))\left(8+29m_L\beta\right)\delta^3\lambda^3+b_{10}}{(16(-1+\delta)(1+\delta(-1+\lambda))+(-8+\delta(8+\lambda))\delta[1-\lambda])}$
D_{2H}	$\frac{-1024(-1+\delta)b_9(4+\delta(-4+\lambda))(1+\delta(-1+\lambda))^3\left(1/2tk^2+m_L\beta\delta\right)+b_{12}}{8\delta(1-\lambda)(4(8+\delta(-8+\lambda))(1+\delta(-1+\lambda))}$
D_{2L}	$\frac{16(-1+\delta)^2\left(83/2tk^2+336(-1+\delta)+m_L\beta b_7\right)+8(-1+\delta)\delta}{8\delta[1-\lambda](4(8+\delta(-8+\lambda))(1+\delta(-1+\lambda)}$
π_r	$\frac{1}{256}\left(\frac{2\left(tk^2+4b_{10}\right)}{b_{14}(7\delta-8)(\delta-1)}-\frac{b_{13}\left(-7tk^2-64\delta\right)}{8(4+\delta\lambda)(\lambda-1)}-\frac{b_{12}(-6+26\delta-17k\delta)}{b_{14}{}^2(1+\delta(-1+\lambda))}\right.$
π_m	$\frac{(1-\delta)b_7b_{12}(8-\lambda)+\delta b_{13}b_{14}(-1+\delta)^3-b_9m_L\beta(4+\delta(-2-2k+\lambda))}{16\delta(8-7\delta)^2(4-3\delta)^2(20+(20-7\lambda))}$

6.2. Scenario HDD

In this scenario, the supply chain adopts a dual-rollover strategy. The supplier enhances the product's quality through AI-driven upgrades while continuing to offer the original version in the second period, and the retailer fully discloses the complete specifications and availability information for both product generations during the first period. In the first period, the consumers' utility is $U_1 = v + \beta m_\iota - p_1$. In the second period, the consumers' utility for purchasing the non-upgraded product is $U_{2H} = \delta\left(v + \beta m_H\right) - P_{2H}$, and the consumers' utility for purchasing the non-upgraded product is $U_{2L} = \lambda\delta\left(v + \beta m_L\right) - P_{2L}$. If $U_1 \geq \max\left\{U_{2H}, U_{2L}, 0\right\}$, the consumers decide to purchase in the first period; otherwise, they delay purchasing the product. In the second period, if $U_{2n} \geq \max\left\{U_1, U_{2L}, 0\right\}$, the consumers will purchase the upgraded product. If $U_{2L} \geq \max\left\{U_1, U_{2L}, 0\right\}$, they will purchase the non-upgraded product; otherwise, they will not purchase. When the supplier upgrades the product and discloses the quality information, the demand functions of the first and second periods are derived as follows.

The demand function in the first period is

$$D_1 = 1 - \frac{\delta\beta m_H - \beta m_L + p_1 - p_{2H}}{1-\delta}. \tag{6.6}$$

The demand function in the second period is

$$D_{2H} = \frac{\delta\beta m_H - \beta m_L + p_1 - p_{2H}}{1-\delta} - \frac{\lambda\delta\beta m_L - \delta\beta m_H + p_{2H} - p_{2L}}{\delta(1-\lambda)} \tag{6.7}$$

$$D_{2L} = \frac{\lambda\delta\beta m_L - \delta\beta m_H + p_{2H} - p_{2L}}{\delta(1-\lambda)} - \frac{p_{2L} - \lambda\delta\beta m_L}{\lambda\delta}. \tag{6.8}$$

In this scenario, the supplier chooses not to upgrade the product and does not disclose the quality information. The total profit functions of the supplier and retailer are as follows:

$$\pi_m = w_1 D_1 + \left(w_{2H} - \frac{1}{2}tk^2\right) D_{2H} + w_{2L} D_{2L} \tag{6.9}$$

$$\pi_r = (p_1 - w_1)\, D_1 - c + (p_{2H} - w_{2H})\, D_{2H} + (p_{2L} - w_{2L})\, D_{2L}. \tag{6.10}$$

With backward induction, the optimal solution for Scenario HND is illustrated in Table 8 below.

Table 8. The equilibrium solution under Scenario HD.

HDD	
w_1	$\frac{b_{11}}{4b_{14}(4-3\delta)}$
w_{2H}	$\frac{1}{2}\left(\frac{1}{2}tk^2 + (k-1)m_L\beta\delta + \frac{\delta\,(b_2 + m_L\beta b_3)}{2b_{14}}\right)$
w_{2L}	$\frac{\delta\lambda\,(b_2 + m_L\beta b_3)}{4b_{14}}$
p_1	$\frac{b_2 + m_L\beta b_3}{2b_{14}}$
p_{2H}	$\frac{\frac{1}{2}tk^2(\delta-2)(27\delta-32) + 3b_4}{8b_{14}}$
p_{2L}	$\frac{3\delta\lambda\,(b_2 + m_L\beta b_3)}{8b_{14}}$
D_1	$\frac{b_9}{8(\delta-1)(7\delta-8)}$
D_{2H}	$\frac{b_8 - \frac{1}{2}tk^2 b_5 - m_L\beta\delta\,(b_7 + k\,(64 + b_6))}{8\delta b_{14}(\delta-1)(\lambda-1)}$
D_{2L}	$\frac{\frac{1}{2}tk^2 + m_L\beta\delta - km_L\beta\delta}{4\delta - 4\delta\lambda}$
π_r	$\frac{1}{64}\left(-64c + \frac{2b_9 b_{10}}{b_{14}(3\delta-4)(\delta-1)} - \frac{b_{13}}{b_{14}(\lambda-1)} - \frac{b_{12}}{{b_{14}}^2(\delta-1)\delta(\lambda-1)}\right.$
π_m	$\frac{\delta b_9 b_{11}(1-\lambda) + \delta b_{13} b_{14}(1-\delta) - b_{12}}{32\delta(8-7\delta)^2(4-3\delta)^2(\delta-1)(\lambda-1)}$

6.3. Comparative Analysis of the Dual-Rollover and Single-Rollover Strategies

In the dual-rollover scenario, we study the impact of upgrading the AI innovation level and the innovation cost on the supplier's wholesale price and profit, and the impact on the retailer's profit, and compare it with the single-rollover scenario.

Proposition 6.3.1. (i) $w_1^{HDD} < w_1^{HND}, w_{2H}^{HDD} < w_{2H}^{HND}, w_{2L}^{HDD} < w_{2L}^{HND}$.

(ii) $w_1^{HN} > w_1^{HND}, w_1^{HD} < w_1^{HDD}, w_{2H}^{HN} < w_{2H}^{HND}, w_{2H}^{HD} > w_{2H}^{HDD}$.

(iii) $p_1^{HDD} < p_1^{HND}, p_{2H}^{HDD} < p_{2H}^{HND}, p_{2L}^{HDD} < p_{2L}^{HND}$.

(iv) $p_1^{HN} > p_1^{HND}, p_1^{HD} < p_1^{HDD}, p_{2H}^{HN} < p_{2H}^{HND}, p_{2H}^{HD} > p_{2H}^{HDD}$.

Proof. See Appendix B.

Proposition 6.3.1 reveals key insights into the pricing dynamics under varying rollover and disclosure strategies. Specifically, in dual-rollover scenarios, where both the upgraded and original products are available concurrently, the suppliers set lower wholesale prices when the upgrade information is disclosed compared with when it is kept confidential. This holds true for both the first-period and second-period pricing of both product versions. When examining the differences between the single- and dual-rollover strategies under nondisclosure conditions, the single-rollover strategy leads to higher first-period prices, whereas the dual-rollover strategy results in higher second-period prices for upgraded products. Conversely, when disclosure is implemented, this pattern reverses: The dual-rollover strategy generates higher first-period prices, while the single-rollover strategy achieves better second-period pricing for upgraded products. The selling price dynamics mirror these wholesale price patterns, indicating consistent intertemporal pricing behavior across the supply chain. These pricing patterns can be attributed to several underlying mechanisms. Disclosure of the quality information enhances consumers' understanding of the product's improvements, leading to more strategic purchasing behavior. Consumers become more inclined to defer purchases in anticipation of upgraded products, compelling suppliers to reduce first-period prices to sustain sales. In dual-rollover scenarios, the simultaneous presence of both product versions fosters direct competition, particularly when disclosure enables clear feature comparisons, resulting in overall price compression.

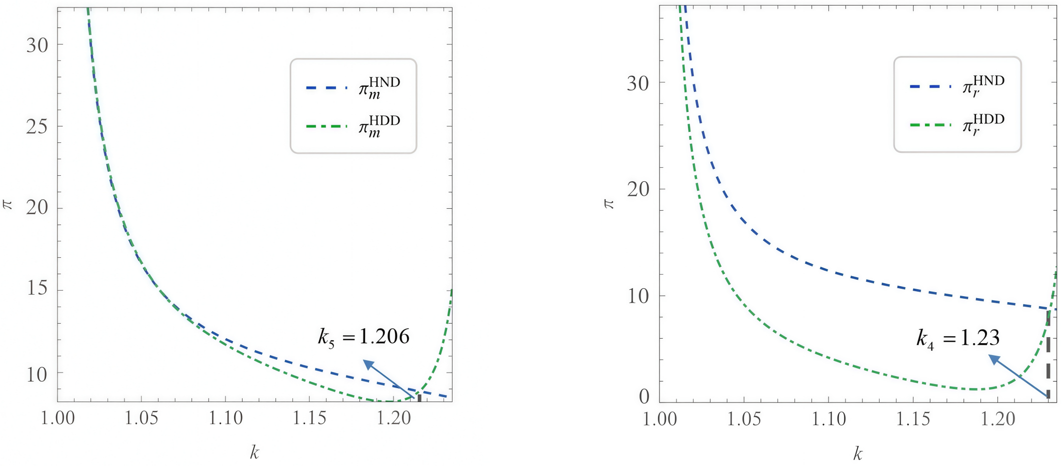
Furthermore, inventory management strategies diverge significantly. The single-rollover strategy benefits from scarcity effects, which bolster price premiums in the second period. In contrast, the dual-rollover strategy necessitates careful price differentiation to mitigate cannibalization between product generations, especially when consumers possess complete information about the upgrades. These findings offer valuable guidance for product managers implementing technological upgrades. For substantial AI-driven improvements, such as new smartphone processor generations, a dual-rollover approach, coupled with selective information disclosure, can maximize profits by effectively catering to both technology enthusiasts and price-sensitive consumers. Conversely, for minor upgrades, like incremental software improvements, a single-rollover strategy with controlled information release is more effective in maintaining pricing power throughout the products' lifecycle. The crucial aspect is to carefully align the rollover and disclosure strategy with the magnitude of the technological advancement and the characteristics of the target consumer segments.

Proposition 6.3.2. (i) If $k \leq k_4$, then $\pi_r^{\text{HND}} \geq \pi_r^{\text{HDD}}$. If $k > k_4$, then $\pi_r^{\text{HDD}} > \pi_r^{\text{HND}}$.

(ii) If $k \leq k_5$, then $\pi_m^{\text{HND}} \geq \pi_m^{\text{HDD}}$. If $k > k_5$, then $\pi_m^{\text{HDD}} > \pi_m^{\text{HND}}$.

Proof. See Appendix B.

From Proposition 6.3.2, it can be seen that distinct profit patterns for retailers and suppliers under dual-rollover strategies. For retailers, when the upgrade level with AI technology (k) falls below the threshold k_4 ($k_4 = 1.23$), nondisclosure generates higher profits than disclosure. However, this relationship reverses when k exceeds k_4 ($k_4 = 1.23$). As demonstrated in Figure 9(a), we clearly present the profit graph under dual-rollover strategies with and without disclosure, with the parameters set as $\beta = 0.8, \gamma = 0.7, \lambda = 0.7, \delta = 0.6, t = 1.5, m_L = 12, c = 1.5$, and $k \in [1, 1.25]$. Similarly for suppliers, as shown in Figure 9(b), non-disclosure yields greater profits when k is below the threshold k_5 ($k_5 = 1.206$), while disclosure becomes more profitable when k surpasses k_5 ($k_5 = 1.206$). These profit dynamics stem from three key factors. First, the cost of achieving an upgrade, which depends on both the upgrade level k and the cost coefficient t, creates different cost-benefit tradeoffs. At lower k levels, the total upgrade cost outweighs the benefits of demand stimulation, while at higher k levels, the enhanced product value justifies the disclosure expenses. Second, consumer uncertainty interacts with disclosure when uncertainty is high, and non-disclosure protects margins by maintaining information asymmetry, but when the products demonstrate substantial AI improvements (high k), disclosure reduces uncertainty and boosts demand. Third, consumers' quality preference becomes more quality-sensitive, as consumers respond more strongly to disclosed information about significant upgrades. These findings suggest that firms should adopt a tiered disclosure strategy for AI product launches. For incremental upgrades (e.g., smartphone camera improvements), where the cost of achieving a higher k may be prohibitive relative to the gain, maintaining confidentiality helps preserve the margins. For breakthrough innovations (e.g., autonomous driving systems) where the performance gain k is substantial, proactive disclosure maximizes profits by reducing consumers' uncertainty and highlighting technological superiority. This approach is particularly relevant for consumer electronics manufacturers managing product portfolios with varying levels of AI advancement.



(a) The impact of k on profits of supplier **(b)** The impact of k on profits of retailer

Figure 9. The impact of k on profits of the supplier and retailer under dual-rollover strategies.

Proposition 6.3.3. (i) If $k \le k_6$, then $\pi_r^{HND} \ge \pi_r^{HN}$. If $k > k_6$, then $\pi_r^{HN} > \pi_r^{HND}$.
(ii) If $\gamma \le \gamma_3$, then $\pi_r^{\mathrm{HND}} \ge \pi_r^{\mathrm{HN}}$. If $\gamma > \gamma_3$, then $\pi_r^{\mathrm{HN}} > \pi_r^{\mathrm{HND}}$.

Proof. See Appendix B.

Proposition 6.3.3 identifies distinct patterns in retailers' profitability across different product rollover strategies, governed by two key thresholds. When the upgrade levels with AI technology remain below the critical threshold k_6, dual-rollover strategies with nondisclosure generate superior retailer profits compared with single-rollover alternatives. Beyond this threshold, the profit advantage shifts to single-rollover strategies with full disclosure. A parallel dynamic emerges regarding consumer uncertainty. Below the uncertainty threshold γ_3, the dual-rollover strategy with non-disclosure proves to be more profitable, while above this threshold, the single-rollover strategy with disclosure becomes the preferred strategy. These patterns reflect fundamental market mechanisms. The cost structure of upgrades with AI technology interacts significantly with the rollover strategy's effectiveness. For minor technological improvements, dual-rollover strategies better amortize the development costs across multiple product generations. More substantial innovations justify the focused approach of the single-rollover strategy, where the premium pricing potential offsets concentrated marketing investments. Consumers' behavior further moderates these relationships. In low-uncertainty environments, dual-rollover strategies successfully address heterogeneous consumer segments through product differentiation. High-uncertainty markets instead reward the clarity and focus of single-rollover strategies, where comprehensive disclosure reduces consumers' hesitation. Technology retailers should implement a structured decision framework that evaluates both the technological significance and market uncertainty. For incremental innovations in stable markets, such as annual smartphone processor upgrades, dual-rollover strategies optimize profitability. For transformative technologies entering uncertain markets, like the initial AI-driven home assistants, single-rollover strategies with transparent communication prove more effective. This analytical approach enables retailers to systematically match product introduction strategies to technological and market characteristics.

Proposition 6.3.4. (i) If $k \leq k_7$, then $\pi_r^{HDD} \geq \pi_r^{HD}$. If $k > k_7$, then $\pi_r^{HD} > \pi_r^{HDD}$.

(ii) If $\gamma \leq \gamma_4$, then $\pi_r^{HDD} \geq \pi_r^{HD}$. If $\gamma > \gamma_4$, then $\pi_r^{HD} > \pi_r^{HDD}$.

Proof. See Appendix B.

Proposition 6.3.4 indicates that when the upgrade levels with AI technology remain below the critical threshold k_7, dual-rollover strategies with nondisclosure generate superior retailer profits compared with single-rollover alternatives. Beyond this threshold, the profit advantage shifts to single-rollover strategies with full disclosure. Below the uncertainty threshold γ_4, the dual-rollover strategy with non-disclosure proves more profitable, while above this threshold, the single-rollover with disclosure becomes the preferred strategy.

7. Extensions

7.1. Considering the AI investment level

In this section, we extend the model by endogenizing the supplier's adoption of AI technology to upgrade quality, with the level of AI investment denoted by an additional superscript L. Following Liu et al. [34] and Niu et al. [35], when the supplier invests in AI technology, the product's quality can be upgraded to a higher level, denoted $m_H = m_L + \eta k$, where η represents the quality improvement factor brought by AI technology and k reflects the level of AI investment. A larger value of η indicates the higher effectiveness of AI technology in improving the product's quality.

Furthermore, building on the conceptual link suggested in the existing literature, such enhanced product quality through AI investment can, in turn, strengthen consumers' trust in the product. To formally capture this trust-enhancing effect, we introduce a Bayesian updating mechanism, where AI investment also elevates the credibility of quality disclosures through the trust function $\tau(k) = \tau_0 + \alpha k$, with τ_0 representing the baseline trust probability without AI support and α denoting the marginal trust enhancement coefficient. From a supply chain management perspective, the trust function $\tau(k)$ reflects the extent to which AI-supported monitoring and verification reduce information asymmetry and limit opportunistic disclosure behavior, thereby making the disclosed quality information more credible to the consumers.

In the case without disclosure (HN), consumers rely solely on their prior uncertainty parameter μ, forming the expectations $E[m_2] = m_L + \mu\eta k$. In contrast, in the case of disclosure (HD), consumers update their beliefs according to Bayesian principles: With probability $\tau(k)$, they believe in the disclosed quality $m_H = m_L + \eta k$, and with probability $1 - \tau(k)$, they retain their prior expectation $m_H = m_L + \mu\eta k$. This leads to the posterior expected quality $E[m_2] = \tau(k)(m_L + \eta k) + (1 - \tau(k))(m_L + \mu\eta k)$. Intuitively, a higher value of $\tau(k)$ implies that consumers place greater weight on AI-enabled disclosures and rely less on subjective prior beliefs, capturing the trust-building role of AI investment in a parsimonious manner.

Through a comparative equilibrium analysis of the HNL (upgrade, no disclosure, endogenous investment) and HDL (upgrade, disclosure, endogenous investment) scenarios, we examine how AI investment generates synergistic effects through both quality enhancement and trust-building channels, the thereby reshaping the strategic interactions between technological upgrading and information transparency in AI-driven supply chains.

7.1.1. Scenario HNL

Following the demand structure established in Section 4, $U_1 = v + \beta m_L - p_1, E[m_2] = m_L + \mu\eta k, U_2 = \delta(v + \beta E[m_2]) - p_2$, we can conclude that the first-period's demand function is

$$D_1 = 1 - \frac{\delta\beta E[m_2] - \beta m_L + p_1 - p_2}{1 - \delta}. \tag{7.1}$$

The first-period's demand function is

$$D_1 = \frac{\delta\beta E[m_2] - \beta m_L + p_1 - p_2}{1 - \delta} - \frac{p2 - \delta\beta E[m_2]}{\delta}. \tag{7.2}$$

The corresponding profit functions of the supplier and the retailer are reported in Equations (7.3) and (7.4), respectively.

$$\pi_m = w_1 D_1 + w_2 D_2 - \frac{1}{2}tk^2 \tag{7.3}$$

$$\pi_r = (p_1 - w_1) D_1 + (p_2 - w_2) D_2. \tag{7.4}$$

With backward induction, the optimal solution for Scenario HNL is illustrated in Table 9 below. In this scenario, AI investment affects market outcomes only through direct quality improvement, as the absence of disclosure prevents the activation of the trust-building channel.

Table 9. The equilibrium solution under Scenario HNL.

HNL	
k^*	$\frac{2\beta\,(1+m_L\beta)\,(1-\delta)\delta(48+\delta(31\delta-78))\eta\mu}{8t(4-3\delta)^2(1-\delta)(8-7\delta)-\beta^2\delta(256-\delta(636+\delta(-524+143\delta)))h^2\mu^2}$
w_1	$\frac{2\,(1+m_L\beta)\,(\delta-1)(128+\delta(79\delta-200))+k^*\beta\delta(32+\delta(23\delta-54))\eta\mu}{4(4-3\delta)^2(7\delta-8)}$
w_2	$\frac{2\,(1+m_L\beta)\,(1-\delta)\delta(24-19\delta)+k^*\beta\delta(64-\delta(110-47\delta))\eta\mu}{4(4-3\delta)(8-7\delta)}$
p_1	$\frac{2\,(1+m_L\beta)\,(1-\delta)(24-19\delta)-k^*\beta\delta(6-5\delta)\eta\mu}{2(4-3\delta)(8-7\delta)}$
p_2	$\frac{6\,(1+m_L\beta)\,(1-\delta)\delta(24-19\delta)+3k^*\beta\delta(64-\delta(110-47\delta))\eta\mu}{8(4-3\delta)(8-7\delta)}$
D_1	$\frac{2\,(1+m_L\beta)\,(1-\delta)(8-9\delta)-k^*\beta\delta(10-9\delta)\eta\mu}{8(1-\delta)(8-7\delta)}$
D_2	$\frac{2\,(1+m_L\beta)\,(1-\delta)(24-19\delta)+k^*\beta(64-(110-47\delta)\delta)\eta\mu}{8(1-\delta)(4-3\delta)(8-7\delta)}$
π_r	$\frac{4\,(1+m_L\beta)^2\,(8-5\delta)^2(1-\delta)^2-4k\beta\,(1+m_L\beta)\,M_1\eta\mu-k^2\left(8t(4-3\delta)^2(1-\delta)(8-7\delta)-\beta^2M_2\eta^2\mu^2\right)}{(16(4-3\delta)^2(1-\delta)(8-7\delta))}$
π_m	$\frac{4\,(1+m_L\beta)^2\,M_3-4k^*\beta(1+mL\beta)M_4\eta\mu+k^{*2}\beta^2\delta(-4096+\delta(13760+\delta(-17388+(9804-2083\delta)\delta)))\eta^2\mu^2}{64(8-7\delta)^2(4-3\delta)^2(-1+\delta)}$

7.1.2. Scenario HDL

Following the demand structure established in Section 4, $U_1 = v+\beta m_L-p_1, E\left[m_2\right] = \tau(k)\left(m_L+\eta k\right)+ (1-\tau(k))\left(m_L+\mu\eta k\right), U_2 = \delta\left(v+\beta E\left[m_2\right]\right)-p_2$, we can conclude that the first-period's demand function is

$$D_1 = 1-\frac{\delta\beta E\left[m_2\right]-\beta m_L+p_1-p_2}{1-\delta} \tag{7.5}$$

The first-period's demand function is

$$D_1 = \frac{\delta\beta E\left[m_2\right]-\beta m_L+p_1-p_2}{1-\delta}-\frac{p2-\delta\beta E\left[m_2\right]}{\delta}. \tag{7.6}$$

The corresponding profit functions of the supplier and the retailer are reported in Equations (7.7) and (7.8), respectively.

$$\pi_m = w_1D_1+w_2D_2-\frac{1}{2}tk^2 \tag{7.7}$$

$$\pi_r = \left(p_1-w_1\right)D_1+\left(p_2-w_2\right)D_2-c \tag{7.8}$$

With backward induction, the optimal solution for Scenario HDL is illustrated in Table 10 below. Under disclosure, AI investment simultaneously enhances the product's quality and strengthens the credibility of disclosure, thereby generating an additional trust-based return that is absent in the HNL scenario.

Table 10. The equilibrium solution under Scenario HDL.

HDL	
k^*	$\dfrac{2\beta\tau_0\,(1+m_L\beta)\,(1-\delta)\delta(47+\delta(6\delta-5))\eta^2\mu}{(4-3\delta)^2(8-7\delta)-\beta^2\,(256-\delta\,(\tau_0+\delta(-24+5\delta)))\,\eta^2\mu^2}$
w_1	$\dfrac{\left(-256+2m_L\beta M_5+\delta\left(656+32M_6+18\delta\,(-31+3M_6)+\delta^2\,(158+23M_6)\right)\right)}{4(4-3\delta)^2(-8+7\delta)}$
w_2	$\dfrac{\frac{1}{2}\delta\,(M_6+(48+2m_L\beta(-1+\delta)(-24+19\delta)+\delta\,(-86-6M_6+\delta\,(38+5M_6)))}{(2(-4+3\delta)(-8+7\delta))}$
p_1	$\dfrac{(48+2m_L\beta(-1+\delta)(-24+19\delta)+\delta\,(-86-6M_6+\delta\,(38+5M_6)))}{(2(-4+3\delta)(-8+7\delta))}$
p_2	$\dfrac{\left(3\delta\left(48+2m_L\beta(-1+\delta)(-24+19\delta)+64M_6+2\delta\,(-43-55M_6)+\delta^2\,(38+47M_6)\right)\right)}{(8(-4+3\delta)(-8+7\delta))}$
D_1	$\dfrac{(16+2m_L\beta(-1+\delta)(-8+9\delta)+\delta\,(-34-10M_6+9\delta\,(2+M_6)))}{8(-1+\delta)(-8+7\delta)}$
D_2	$\dfrac{\left(-48-2m_L\beta(-1+\delta)(-24+19\delta)-64M_6+\delta^2\,(-38+47M_6)+2\delta\,(43+55M_6)\right)}{(8(-1+\delta)(-4+3\delta)(-8+7\delta))}$
π_r	$\dfrac{\delta\,(M_7+M_6M_{15})^2+2(8-7\delta)\,(M_9+\delta\,((9\delta+10)M_6+18\delta-34)) \times (M_8+\delta\,(10\delta-26+(2+\delta)M_6))}{64(8-7\delta)^2(4-3\delta)^2(1-\delta)}-c$
π_m	$\dfrac{M_{11}+k^{*4}\alpha^2\beta^2\delta M_{10}\eta^2(\mu-1)^2+\left(2k^{*3}\alpha\beta^2\delta M_{10}\eta^2(\mu-1)-4k^*M_{12}\beta\eta\right)M_{13} + k^{*2}\left(M_{14}+\beta\delta\eta\left(M_{12}+\beta M_{10}\eta M_{13}^2\right)\right)}{16(8-7\delta)^2(4-3\delta)^2(1-\delta)}$

7.2. Comparative Analysis

7.2.1. Analysis of Supply Chain Decisions under Endogenous AI Investment

Building on the equilibrium outcomes derived from the extended model with endogenous AI investment, this subsection comparatively examines how the interplay between AI-driven upgrading and quality disclosure influences supply chain-related decisions and profits. The following propositions and numerical analysis reveal the nuanced effects of AI-driven-related trust enhancement on investment incentives and disclosure strategies.

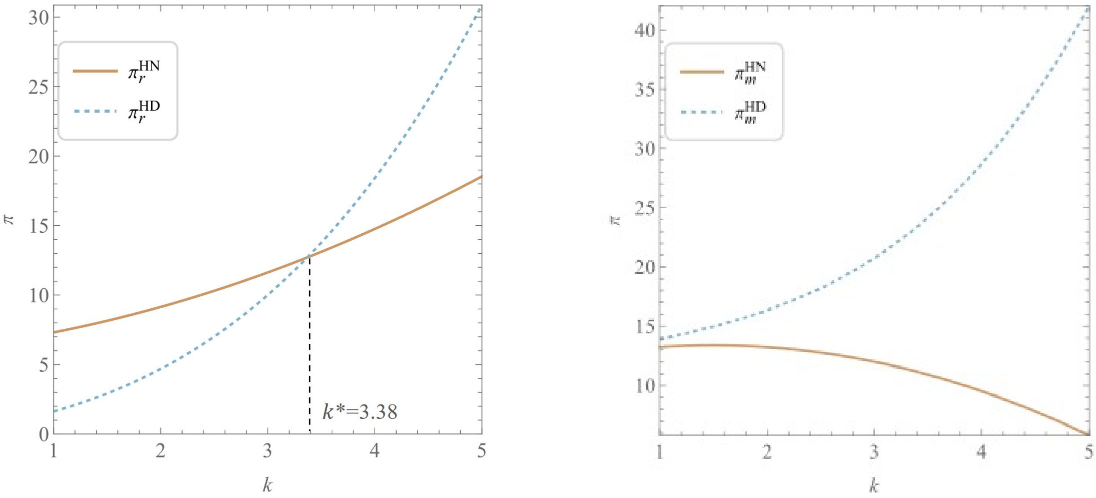
Proposition 7.2.1. (i)When $\alpha < \alpha^*, k^{HNL} > k^{HDL}$. (ii) When $\alpha > \alpha^*, k^{HDL} > k^{HNL}$.

Proposition 7.2.1 reveals the influence mechanism of retailer's product quality disclosure behavior on AI technology investment decisions. At a high level, this proposition shows that AI investment becomes more attractive when disclosure allows its trust-enhancing effect to be internalized by the market, whereas without disclosure, the investment returns are dampened by persistent consumer uncertainty. In situations where the product's quality is undisclosed, suppliers bear higher decision-making risks due to market information asymmetry. This makes the investment more susceptible to the consumers' belief biases and market demand fluctuations, thus resulting in a more conservative investment approach. In contrast, when retailers disclose the product's quality, the information structure within the supply chain is optimized, facilitating effective communication between suppliers and the market. The result can be understood through two opposing forces. First, disclosure may intensify strategic consumer waiting, which weakens investment incentives by shifting demand to later periods. Second, disclosure activates the trust-building channel of AI investment, amplifying consumers' perceived quality gains. The net effect depends on the trust-enhancement efficiency. When the trust-enhancement efficiency is small, the strategic waiting effect dominates; once it exceeds a critical threshold, the trust-amplification effect outweighs the delay effect, making disclosure investment-enhancing.

These findings imply that (i) in the absence of product quality disclosure by retailers, suppliers must carefully plan the scale of AI technology investment to avoid inefficiencies caused by unclear information; (ii) in the context of product quality disclosure, retailers provide suppliers with a clearer framework for recognizing investment value, potentially supporting the rationale for higher levels of AI technology investment. These insights are significant for understanding the collaborative application of AI technology and information disclosure within supply chains, highlighting how trust-driven disclosure can align technological upgrading with market transparency to enhance supply chains' innovation and performance.

Proposition 7.2.2 (i) When $k < k^*, \pi_r^{HN} > \pi_r^{HN}, k > k^*$, and $\pi_r^{HD} > \pi_r^{HN}$. (ii) $\pi_m^{HD} > \pi_m^{HN}$.

Proposition 7.2.2 reveals the asymmetric impact of disclosure on supply chain members' profitability under endogenous AI investment. For the retailer, the decision to disclose is contingent on the scale of AI investment: When investment is modest, the retailer prefers to withhold quality information to avoid triggering pronounced strategic waiting; when investment is substantial, the retailer benefits from transparency because the trust-enhanced quality perception stimulates sufficient demand to offset intertemporal cannibalization. In contrast, the supplier unambiguously gains from disclosure at any investment level. Because disclosure not only elevates consumers' willingness to pay through the trust channel but also improves the channel's coordination by aligning second-period pricing with actual quality realization. This divergence in preferences highlights a potential incentive misalignment between the supplier and the retailer regarding information disclosure: The supplier always favors transparency, whereas the retailer supports disclosure only when AI investment is sufficiently high. The retailer's profit comparison follows from the trade-off between expended demand through enhanced trust under disclosure and the potential demand erosion due to strategic waiting. For a low level of AI investment, the trust-building effect is weak, and early disclosure mainly intensifies consumer delays, reducing the retailers' intertemporal revenue. Once the level of AI investment surpasses k^*, the trust-amplification channel becomes strong enough to outweigh the strategic delay effect, making disclosure more profitable for the retailer. For the supplier, disclosure always improves profit because it simultaneously boosts the perceived quality and mitigates the double-marginalization distortion in the second period; these benefits dominate any negative demand-shifting effect, leading to a strict profit advantage under HD regardless of the investment level. These findings underscore the importance of coordinating disclosure policies with technology investment levels to ensure that both supply chain members benefit from AI-driven quality upgrading, thereby fostering more effective collaboration in the supply chains with AI technology.



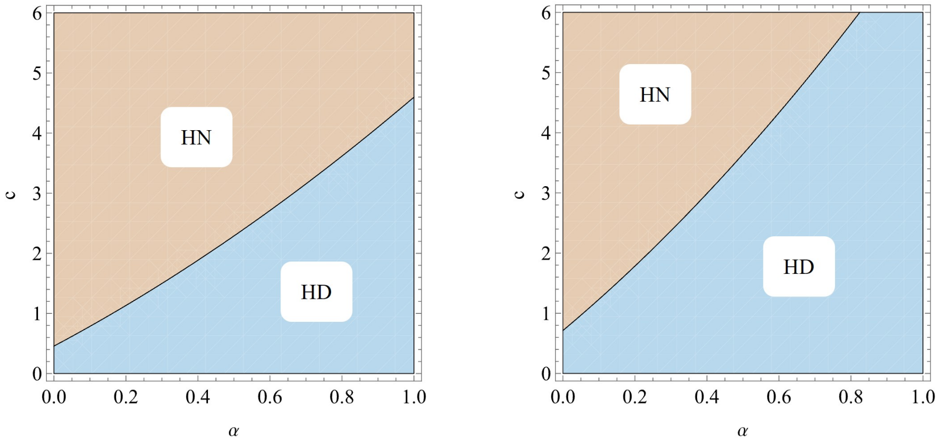
(a) The impact of k on retailers' profits **(b)** The impact of k on suppliers' profits

Figure 10. The impact of k on profits considering the AI investment level.

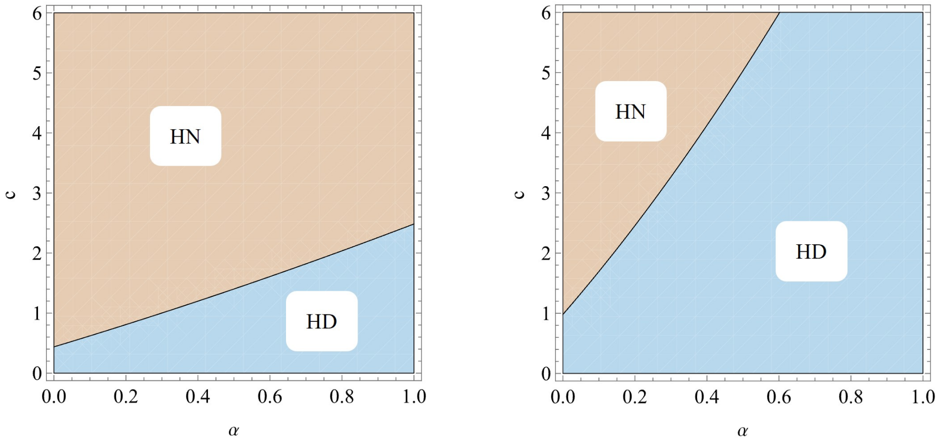
7.2.2. Analysis of retailers' quality disclosure decisions

To test the robustness of the core conclusions and examine the retailer's product quality disclosure decision in the context of endogenous AI technology, we conduct a numerical analysis to compare the retailer's profit performance under two different scenarios, with the parameters set to $\beta = 0.8 and \delta = 0.6$.

Figure 10(a) illustrates that under the assumption of endogenous AI technology, the retailer's optimal disclosure strategy depends critically on the interaction between the trust-enhancement efficiency, the quality improvement factor, and the disclosure cost. Figure 11(a) demonstrates that for a fixed $\mu = 0.6$ and an investment cost coefficient $t = 2.5$, the retailer prefers the HD (disclosure) strategy when the trust-enhancement efficiency is sufficiently high and the disclosure cost is sufficiently low. Specifically, higher trust-enhancement efficiency strengthens the trust-building effect of AI investment, making disclosure more effective in boosting perceived quality, while lower disclosure cost reduces the direct cost burden of information disclosure. Once the trust-enhancement efficiency falls below a threshold or the disclosure cost exceeds a critical level, the retailer reverts to the HN (non-disclosure) strategy. As shown in Figure 11(b), when the quality improvement factor increases from 0.6 to 0.8 (with $\eta = 3$ and $t = 2.5$), the region where HD dominates expands substantially. A higher quality improvement factor implies that AI investment yields greater actual quality enhancement, which, when combined with disclosure, creates a stronger market premium. Even under moderate uncertainty and disclosure cost levels, the consumers'increased willingness to pay justifies the disclosure expense, leading the retailer to favor HD over a wider parameter range. Figure 11(c) illustrates that an increase in the AI technology effectiveness coefficient (from 3 to 4, with $\mu = 0.6$ and $t = 2.5$) similarly increases the HD-favorable region. A higher AI technology effectiveness coefficient reflects the more efficient translation of AI investment into quality and trust gains, reinforcing the positive feedback between investment and disclosure profitability. Finally, Figure 11(d) indicates that an increased AI investment cost coefficient (from 2.5 to 3, with $\mu = 0.6$ and $\eta = 3$) shrinks the area where HD is preferred. Elevated investment costs reduce the net return from AI upgrading, thereby dampening the synergistic value of disclosure and making the retailer more cautious about incurring additional disclosure costs. In summary, the retailer's disclosure incentive is strengthened by higher trust-enhancement efficiency, greater quality improvement capability, and lower disclosure costs, but is weakened by higher AI investment costs. These findings highlight that the profitability of disclosure is not determined by a single parameter but by the interplay between AI's technological effectiveness, trust-building capacity, and the cost structure of both investment and information disclosure.



(a) $\mu = 0.6, \eta = 3, t = 2.5$ **(b)** $\mu = 0.6, \eta = 4, t = 2.5$



(c) $\mu = 0.8, \eta = 3, t = 2.5$ **(d)** $\mu = 0.6, \eta = 3, t = 3$

Figure 11. The impact of α and c on the retailer's profits, considering the AI investment level.

In practice, retailers' disclosure decisions are synergistically affected by technological effectiveness, trust-building outcomes, and cost structures, showing distinct adaptability to different contexts. First, when AI investment significantly enhances consumers' trust and disclosure costs are low, retailers tend to adopt disclosure to maximize profits. This holds if AI technology investment converts to trust premiums with controllable implementation costs. Furthermore, stronger AI-driven quality improvement expands disclosure's applicability; even with moderate disclosure costs, it remains optimal if AI delivers prominent quality and trust. However, when the enterprises are at high-quality improvement levels, disclosure's profitability only stabilizes under low costs and high trust enhancement. Finally, higher AI investment costs constrain the willingness to disclose information; non-disclosure is preferable if the costs are high or AI's trust enhancement is limited. This highlights that AI investment must align with the cost-benefit balance to avoid ineffective blind investment. In conclusion, retailers' disclosure decisions are essentially a dynamic trade-off among AI-enabled value, benefits, and costs, requiring flexible adaptation to firms' AI technology effects and cost structures. In particular, the trust parameter provides a concise link between the intensity of AI investment and market-recognized disclosure credibility.

8. Conclusion

We consolidate the study's theoretical contributions and practical implications regarding AI-driven quality upgrades in supply chains, while identifying critical limitations to guide future research directions.

8.1. Main findings

This paper develops a two-period supply chain model, composed of a supplier, a retailer, and consumers, motivated by the increasing integration of AI technology in manufacturing and retail operations. While the model is anchored in AI applications, its key insights are generalizable to other credibility-enhancing data-driven technologies, with AI serving as a critical motivating context. The framework captures the strategic interactions among AI-driven quality upgrades, information disclosure strategies, and consumers' decision-making under varying degrees of uncertainty. By analyzing equilibrium outcomes across four benchmark scenarios (LN, LD, HN, HD) and two dual-rollover settings (HND, HDD), the study aims to identify the optimal upgrade and disclosure strategies for supply chain participants.

The results reveal that the supplier's upgrade decision is primarily contingent upon the level of AI-driven quality improvement. Specifically, when the upgrade intensity remains below a critical threshold, the marginal benefit derived from quality enhancement fails to adequately offset the associated implementation costs, rendering non-upgrade strategies more economically viable. Conversely, once the upgrade level surpasses this threshold, the resulting gains in the product's performance and demand justify the AI investment. Therefore, suppliers should strategically pursue AI-driven upgrades only when the technological improvements are substantial enough to compensate for the costs, whereas marginal enhancements should be deferred to prevent potential margin erosion.

For retailers, disclosure decisions are significantly shaped by the consumers' quality preference and the level of perceived uncertainty. Disclosure enhances transparency and stimulates early purchasing when consumers exhibit high sensitivity to quality or when uncertainty is low. However, in conditions of high uncertainty or a preference for low quality, non-disclosure becomes the preferable strategy, as it mitigates strategic waiting behaviors among consumers and stabilizes short-term profitability. These findings delineate the boundary conditions under which disclosure provides a strategic advantage.

Furthermore, when the AI investment level is treated as endogenous within the Bayesian trust-updating framework, the results reveal a self-reinforcing feedback loop between AI investment and information disclosure. In the absence of disclosure, persistent information asymmetry increases the perceived market risk, resulting in restrained investment behavior. In stark contrast, when disclosure is implemented, it not only improves market transparency but also activates the trust-enhancement channel of AI investment, where higher investment directly boosts the credibility of the disclosed information. This credibility amplifies consumers' effective quality perception, which, in turn, increases their willingness to pay and strengthens the economic justification for further AI investment. Thus, disclosure transforms AI's adoption from a cost-centric undertaking into a trust-driven value-creation cycle, wherein investment and disclosure mutually reinforce each other.

Finally, a comparison between single- and dual-rollover strategies demonstrates that dual-rollover structures yield superior profitability at extremely low or high AI upgrade levels. In contrast, single-rollover strategies perform better at intermediate levels of AI upgrade. This contrast provides a valuable benchmark for understanding how the intensity of AI upgrades shape market segmentation, intertemporal pricing strategies, and profit distribution across successive product generations. It is worth noting that while our study is grounded in the context of AI technology due to its growing relevance and dual capability of enhancing both quality and transparency, the core strategic insights regarding the interplay among technology upgrades, disclosure, and consumer trust may extend to other digital or data-driven technologies that enhance information credibility, such as IoT-enabled traceability or blockchain verification systems.

8.2. Managerial implications

This section outlines the key managerial insights derived from our study on AI-driven quality upgrades in supply chains and provides actionable recommendations for firms, retailers, and policymakers.

From a managerial perspective, firms should integrate AI investment, information disclosure, and pricing strategies in accordance with their technological capability and market environment. Notably, these strategic insights are not limited to AI and are equally applicable to other credibility-enhancing data-driven technologies, with AI serving as a representative application scenario. For incremental AI upgrades with low intensity (e.g., algorithmic optimization or partial automation), adopting a non-disclosure strategy helps maintain premium pricing and prevent premature demand substitution. In contrast, for breakthrough AI innovations (e.g., predictive quality analytics or autonomous decision systems), disclosure combined with flexible or penetration pricing can accelerate their adoption and reduce consumers' hesitation.

Retailers should design adaptive disclosure strategies aligned with their consumers' characteristics and the products' maturity. Transparent disclosure is recommended for mature products with low uncertainty to strengthen consumer trust, whereas staged or delayed disclosure is more suitable for emerging AI-driven products facing high uncertainty. Effective coordination between suppliers and retailers is essential to ensure that upgrades' timing and information strategies are mutually reinforcing, thereby maximizing collective profitability.

When AI investment is endogenously determined within a trust feedback framework, managers should recognize that disclosure communicates quality and shapes the return on AI investment itself. This creates a strategic imperative to design AI capability and transparency roadmaps. Furthermore, the endogenous investment model reveals a critical alignment challenge. The supplier's optimal disclosure strategy may differ from the retailer's, especially when AI investment is moderate. To bridge this incentive gap, supply chain partners should consider contractual mechanisms that link disclosure commitments to investment levels. For example, a supplier might offer a wholesale price discount in exchange for the retailer's agreement to disclose AI-driven quality data, ensuring that the trust-enhancement loop is activated even when the retailer's standalone disclosure incentive is weak. Such coordination turns transparency from a tactical choice into a strategic lever that boosts the entire chain's return on AI technology.

From a policy standpoint, governments should develop AI subsidy programs that simultaneously promote innovation and responsible disclosure. Well-calibrated subsidies can alleviate firms' initial investment burdens while preventing excessive market competition caused by premature transparency. Furthermore, transparency regulations should aim to enhance consumers' confidence without discouraging technological advancement, fostering a sustainable ecosystem where AI-driven quality enhancement and information disclosure evolve in balance.

8.3. Future research

Future research could extend this study in several key directions. First, a more nuanced understanding of AI's adoption could be achieved by incorporating a firm's digital drive and digital culture, revealing how organizational readiness impacts the success of AI-driven upgrades. Second, exploring the cost-sharing mechanisms in AI's adoption, such as shared costs for upgrades or disclosures, could provide a more profound understanding of the dynamics of profitability and collaboration in supply chains. Additionally, future work could examine more granular AI cost structures—such as fixed setup costs, data acquisition expenses, or scalability constraints—to better capture the economic realities of AI's implementation and their impact on upgrade and disclosure strategies. Third, future investigations could examine how ethical considerations, particularly data privacy concerns, moderate the effectiveness of AI-driven disclosure strategies. Finally, research could investigate the optimal level and timing of disclosure, moving beyond a binary choice, to offer insights into how firms can strategically balance transparency, consumer trust, and competitive advantage in AI-driven environments.

Author contributions

Both authors contributed equally to this work.

Use of Generative-AI tools declaration

The authors declare that they did not utilize any artificial intelligence (AI) tools in the creation of this article.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (No. 71901141), the Shanghai Planning Project of Philosophy and Social Science (No. 2025EGL015), and the Shanghai Soft Science Research Project (No. 23692110500).

References

1. W. Zheng, B. Li, D. Song, Y. Li, Innovative development strategy of a risk-averse firm considering product unreliability under competition, *Transp. Res. Part E Logist. Transp. Rev.*, **172** (2023), 102970. https://doi.org/10.1016/j.tre.2022.102970
2. *Case study—PlayStation*, Medium, 2024. Available from: `https://medium.com/@nareshnavinash/case-study-playstation-9545d11314b2`.
3. W. Niu, J. Chen, Z. Liu, L. Guan, L. Zhang, Managing product upgrades and rollover under demand uncertainty, *Comput. Ind. Eng.*, **174** (2022), 108762. https://doi.org/10.1016/j.cie.2022.108762
4. M. Zhao, C. Dong, T. C. E. Cheng, Quality disclosure strategies for small business enterprises in a competitive marketplace, *Eur. J. Oper. Res.*, **270** (2018), 218–229. https://doi.org/10.1016/j.ejor.2018.03.030
5. Z. Li, F. Xie, H. Zhang, H. Zhang, Signaling quality through price guarantee window for technology-related products, *Eur. J. Oper. Res.*, **313** (2024), 1154–1168. https://doi.org/10.1016/j.ejor.2023.09.007
6. Y. Liu, B. Shen, D. Ivanov, Product upgrade and advanced quality disclosure in a supply chain, *Comput. Ind. Eng.*, **198** (2024), 110693. https://doi.org/10.1016/j.cie.2024.110693
7. Y. Yu, Y. He, X. Guo, D. Li, H. Huang, Quality disclosure strategy with asymmetric demand information in food supply chains, *Transp. Res. Part E Logist. Transp. Rev.*, **183** (2024), 103427. https://doi.org/10.1016/j.tre.2024.103427
8. Y. Jiang, X. Guan, Y. Bian, S. Huang, Information disclosure with endogenous channel structure, *Nav. Res. Logist.*, **70** (2023), 105–120. https://doi.org/10.1002/nav.22080
9. L. Hao, Y. Tan, Who wants consumers to be informed? Facilitating information disclosure in a distribution channel, *Inf. Syst. Res.*, **30** (2019), 34–49. https://doi.org/10.1287/isre.2017.0770
10. J. Wu, W. Lu, X. Ji, The interactions between upstream quality disclosure and downstream entry, *Eur. J. Oper. Res.*, **309** (2023), 545–559. https://doi.org/10.1016/j.ejor.2023.01.053
11. Y. Yu, J. Xu, J. Z. Zhang, Y. D. Liu, M. M. Kamal, Y. Cao, Unleashing the power of AI in manufacturing: Enhancing resilience and performance through cognitive insights, process automation, and cognitive engagement, *Int. J. Prod. Econ.*, **270** (2024), 109175. https://doi.org/10.1016/j.ijpe.2024.109175
12. M. B. Menezes, R. Pinto, Product proliferation, cannibalisation, and substitution: A first look into entailed risk and complexity, *Int. J. Prod. Econ.*, **243** (2022), 108327. https://doi.org/10.1016/j.ijpe.2021.108327
13. W. Jung, J. Peck, M. Palmeira, K. Kim, An unintended consequence of product upgrades: How upgrades can make current consumers feel left behind, *J. Mark. Res.*, **59** (2022), 223–241. https://doi.org/10.1177/00222437221078551
14. J. Garbas, S. Schubach, M. Mende, M. L. Scott, J. H. Schumann, You want to sell this to me twice!? How perceptions of betrayal may undermine internal product upgrades, *J. Acad. Mark. Sci.*, **51** (2023), 286–309. https://doi.org/10.1007/s11747-022-00881-8

15. N. Wiegand, M. Imschloss, Do You Like What You (Can't) See? The differential effects of hardware and software upgrades on high-tech product evaluations, *J. Interact. Mark.*, **56** (2021), 57–73. https://doi.org/10.1016/j.intmar.2021.03.004
16. I. A. Kash, P. B. Key, S. I. Zoumpoulis, Optimal pricing and introduction timing of technology upgrades in subscription-based services, *Oper. Res.*, **71** (2023), 776–797. https://doi.org/10.1287/opre.2022.2364
17. G. Yang, B. He, K. Yuan, Optimal product rollover strategies for successive-generation products: The role of the trade-in program and product characteristics, *Comput. Ind. Eng.*, **179** (2023), 109163. https://doi.org/10.1016/j.cie.2023.109163
18. J. A. Schwarz, B. Tan, Optimal sales and production rollover strategies under capacity constraints, *Eur. J. Oper. Res.*, **294** (2021), 507–524. https://doi.org/10.1016/j.ejor.2021.01.040
19. W. Wang, L. Feng, Y. Li, G. Cai, W. Zhang, Managing demand slowdown: The interplay between trade-ins and quality improvement, *Nav. Res. Logist.*, **70** (2023), 793–810. https://doi.org/10.1002/nav.22129
20. M. Dong, S. Mao, S. Li, Supplier's technology upgrading investment strategy considering product life cycle, *Int. J. Prod. Econ.*, **263** (2023), 108953. https://doi.org/10.1016/j.ijpe.2023.108953
21. A. Srivastava, T. M. Choi, A. Mahajan, V. Roy, Impacts of gray market selling on the supply chain under product upgrade and pricing flexibility decisions, *Nav. Res. Logist.*, **71** (2024), 365–388. https://doi.org/10.1002/nav.22157
22. Q. Huang, J. Ignatius, H. Song, J. Bian, C. Gong, Impact of loyal and new customer segments on product upgrades: The role of quality differentiation through online reviews, *Eur. J. Oper. Res.*, **324** (2025), 231–245. https://doi.org/10.1016/j.ejor.2024.12.045
23. T. Ye, N. Wang, N. Wang, Analysis on product rollover strategies: the innovation level perspective, *Ind. Mark. Manag.*, **88** (2020), 59–69. https://doi.org/10.1016/j.indmarman.2020.04.015
24. B. Niu, J. Dong, F. Xie, The potential of AI-enabled quality control facing high inspection standard in resilient cross-border operations, *Int. J. Prod. Res.*, **64** (2026), 565–583. https://doi.org/10.1080/00207543.2024.2398581
25. J. Liu, X. Zhai, L. Chen, The interaction between product rollover strategy and pricing scheme, *Int. J. Prod. Econ.*, **201** (2018), 116–135. https://doi.org/10.1016/j.ijpe.2018.03.027
26. Y. Xiao, C. Hu, Q. Liu, Managing demand by upgrade programs and markdown pricing with a product rollover, *Nav. Res. Logist.*, **71** (2024), 335–350. https://doi.org/10.1002/nav.22156
27. S. H. Bae, Q. Zhu, J. Sarkis, Supply chain interactions and strategic product deletion decisions: A game-theoretic analysis, *Transp. Res. Part E Logist. Transp. Rev.*, **186** (2024), 103522. https://doi.org/10.1016/j.tre.2024.103522
28. C. H. Wu, J. Y. Lai, Dynamic pricing and competitive time-to-market strategy of new product rollover under a multistage duopoly, *Eur. J. Oper. Res.*, **277** (2019), 138–152. https://doi.org/10.1016/j.ejor.2019.02.012
29. G. Zheng, A. Brintrup, Enhancing supply chain visibility with generative AI: an exploratory case study on relationship prediction in knowledge graphs, *Int. J. Prod. Res.*, **63** (2025), 4943–4965. https://doi.org/10.1080/00207543.2025.2543964

30. M. Zhu, C. Liang, A. C. Yeung, H. Zhou, The impact of intelligent manufacturing on labor productivity: An empirical analysis of Chinese listed manufacturing companies, *Int. J. Prod. Econ.*, **267** (2024), 109070. https://doi.org/10.1016/j.ijpe.2023.109070
31. S. S. Liu, B. J. Ma, W. Zhang, E. T. C. Cheng, X. Li, C. T. Ng, Eliminating information asymmetry in supply chains: Blockchain-driven or not, *Transp. Res. Part E Logist. Transp. Rev.*, **201** (2025), 104208. https://doi.org/10.1016/j.tre.2025.104208
32. J. Ni, Y. Xu, J. Shi, J. Li, Product innovation in a supply chain with information asymmetry: Is more private information always worse? *Eur. J. Oper. Res.*, **314** (2024), 229–240. https://doi.org/10.1016/j.ejor.2023.10.023
33. F. Sun, H. Yang, J. Chen, B. Chen, B. Yu, Information service and quality strategies in a supply chain, *Transp. Res. Part E Logist. Transp. Rev.*, **199** (2025), 104169. https://doi.org/10.1016/j.tre.2025.104169
34. X. Liu, Z. Zhou, M. Hu, F. Zhong, How retailers can gain more profitability driven by digital technology: Live streaming promotion and blockchain technology traceability? *Electron. Commer. Res. Appl.*, **68** (2024), 101445. https://doi.org/10.1016/j.elerap.2024.101445
35. B. Niu, X. Yu, J. Dong, Could AI livestream perform better than KOL in cross-border operations? *Transp. Res. Part E Logist. Transp. Rev.*, **174** (2023), 103130. https://doi.org/10.1016/j.tre.2023.103130

AIMS Press