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ORIGINAL ARTICLE

Quality management in supply chain: Strategic implications and the paradox of AI inspection

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Abstract

Artificial intelligence (AI) has transformed the quality control process with *AI inspection* technology, which reduces the need for costly physical resources and mitigates retail returns. Despite its revolutionizing impact on supply chain quality management, there is a notable gap in research on the implications of a manufacturer's adoption of AI inspection. This article addresses this gap by presenting a two-stage model that explores the consequences of AI inspection adoption for a downstream manufacturer and an upstream supplier. Our results show that higher AI-based inspection accuracy may not always benefit the manufacturer. This is because when the supplier's traditional inspection accuracy falls within an immediate range, the manufacturer's incentive to improve AI inspection accuracy diminishes, and the positive effect of AI inspection on retail returns cannot fully offset the technology expense. Moreover, our study explores the dynamics of technology-sharing strategies between the manufacturer and supplier. Despite potential revenue gains, the manufacturer may hesitate to share technology due to the risk of increased defective products with lower AI inspection accuracy, leading to a paradox where profitability coexists with losses. Surprisingly, the successful collaborative technology-sharing strategy may paradoxically lead to reduced technology investment. This occurs because technology-sharing enables significant marginal cost savings in retail returns, rendering the manufacturer to achieve a comparable inspection level with lower investment. Overall, this research highlights that adopting AI inspection does not guarantee benefits for the supply chain members and can sometimes be detrimental. Our study offers strategic guidance for decision-makers in supply chain quality management.

KEYWORDS
AI inspection, inspection modes, quality management, retail returns, supply chain management, technology-sharing

1 | INTRODUCTION

Artificial intelligence (AI) has empowered manufacturers with the ability to significantly enhance their supply chain management, establishing itself as a pivotal industry trend. Bluewave Consulting predicts that by 2028, the global market for AI in the supply chain industry will reach more than $20 billion (BusinessDIT, 2023). In particular, the adoption of AI in quality management is expected to reach a value of $1084 million by 2031 (Business Research Insights, 2023). Using AI, supply chain stakeholders can enhance process monitoring and improve quality control coordination, ultimately benefiting retail operations (Choi et al., 2022). McKinsey estimates that AI-enhanced supply chain quality management can cut defects by up to 50% and boost on-time delivery by up to 20% (Bauer et al., 2017). Leading companies, including Hewlett Packard Enterprises (HPE) (HPE, 2023), Toyota (Reuters, 2020), and Lenovo (Instrumental, 2023), have adopted AI technology to enhance quality in their supply chains.

Quality management in supply chains is critical for ensuring product reliability and preventing returns during retail (Bondareva & Pinker, 2019). As leaders in the supply chain, manufacturers can work with suppliers to set strict quality standards, including regular inspections, to spot quality issues throughout the supply chain (Hwang et al., 2006).

Traditionally, these quality inspections are performed manually or visually, requiring physical resources. However, manufacturers now have the option to use AI technology for real-time, intelligent decision-making on product quality, known as *AI inspection*. Some manufacturers go further, sharing AI inspection technology with suppliers to boost quality improvements across the supply chain. Despite its growing adoption, limited research exists on the impacts of AI on supply chain quality management, and this need for more attention to AI inspection strategies motivates our research toward helping firms coordinate quality improvement. Our research aims to address the following questions: *How does AI influence quality management in supply chains*, and *how should manufacturers and suppliers adjust to AI for joint quality improvement?*

1.1 | Motivation

Product quality issues can lead to significant retail returns, damaging the brand reputation and increasing operation costs (Dong et al., 2021). The American Society for Quality has found that operation costs related to quality can take up to 40% of a company's revenue (Cavanaugh, 2023). In response, businesses increasingly focus on preventing quality issues and boosting the efficiency of retail operations. This has resulted in the global quality inspection market growing at an annual rate of over 7% (GrandViewResearch, 2021). Specifically, in the aerospace industry, investing $1 in quality inspection can prevent $1000 in retail return costs (Jonble, 2023). This highlights the critical role of quality inspection in avoiding retail returns and protecting corporate profits.

Advancements in technology are leading top companies to adopt AI for quality inspection. By integrating industry cameras and intelligent systems, companies leverage AI to automate the inspection process and intelligently detect defects (Bauer et al., 2017). As is illustrated in Figure 1, an industry camera captures images of products on the inspection line. The AI system then analyzes these images, compares them to quality standards, and identifies defects in real time. This process allows for the automatic approval of good products and the rejection of faulty ones. With less need for human oversight, AI inspection technologies ensure consistent inspection quality across different locations, encouraging their broad implementation.

AI inspection is increasingly used in supply chain quality management due to its effectiveness. For instance, HPE saw a 25% drop in server defects by incorporating AI to detect problems early in the supply chain (HPE, 2023). Despite its proven successes and potential, however, over two-thirds of original equipment manufacturers stick with traditional inspection methods (Cavanaugh, 2023), mainly manual inspection (Federal Aviation Administration, 2023). These facts point to the key strategic decisions faced by manufacturers regarding whether to integrate AI into their quality control operations. One approach is to implement AI inspection exclusively within their own inspection processes. For instance, GE has adopted this strategy, identifying 150% more defects than human inspectors and thus enhancing product quality before retail distribution (Bjerregaard, 2023). Alternatively, manufacturers also have the option to grant their upstream suppliers access to AI inspection technology. This approach, adopted by Lenovo, involves sharing AI inspection tools with suppliers, which intercepts 4% of defects earlier in the supply chain and saves rework costs related to defects by 60%, leading to superior supply chain quality management (Instrumental, 2023). Both AI inspection strategies contribute to quality management, but many manufacturers hesitate to adopt AI inspection (Google Cloud, 2021).

To understand the reasons behind this hesitation, we conducted interviews with three key executives at an engine manufacturing company, located in China. During the interview, the Retail Manager emphasized that AI technology could significantly reduce the high losses of defective product returns. Moreover, the Supply Chain Manager pointed out that quality issues often stem from suppliers' components, which traditional methods fail to catch efficiently, and underscored the potential for AI to improve quality across the supply chain. However, the Chief Information Officer highlighted the substantial investment of AI technology, presenting a practical barrier despite recognizing its benefits in reducing returns. These insights reveal a challenge that uncertainties of technology returns remain major barriers to hindering firms from adopting AI inspection technology and further deciding on an optimal strategy.

Although previous studies have considered traditional inspection strategies in quality management, research has not fully explored manufacturer's strategies for deploying AI inspection throughout the supply chain (Zhang et al., 2022; Zhu et al., 2007). Furthermore, through the interviews, we realized the need for mathematical modeling in guiding firms to quantitatively choose inspection strategies, including technology investment and collaboration with supplier. By addressing this question and its related practical implications for the market, this article aims to provide novel, actionable insights for firms to optimize their supply chain quality management processes.

1.2 | Contribution and key finding

This article explores the strategic interactions between the manufacturer and supplier in a two-level supply chain, analyzing the potential benefits of AI technology under different inspection strategies. As technology advances, the manufacturer can switch from traditional methods to AI-based inspection, aiming to reduce labor costs and retail returns caused by defects. Additionally, the manufacturer could collaborate with the supplier to implement AI inspection, fostering quality improvements across the supply chain. This cooperative approach seeks to address uncertainties faced by the supplier and minimize defect-related losses in the retail market. To the best of our knowledge, it is the first attempt

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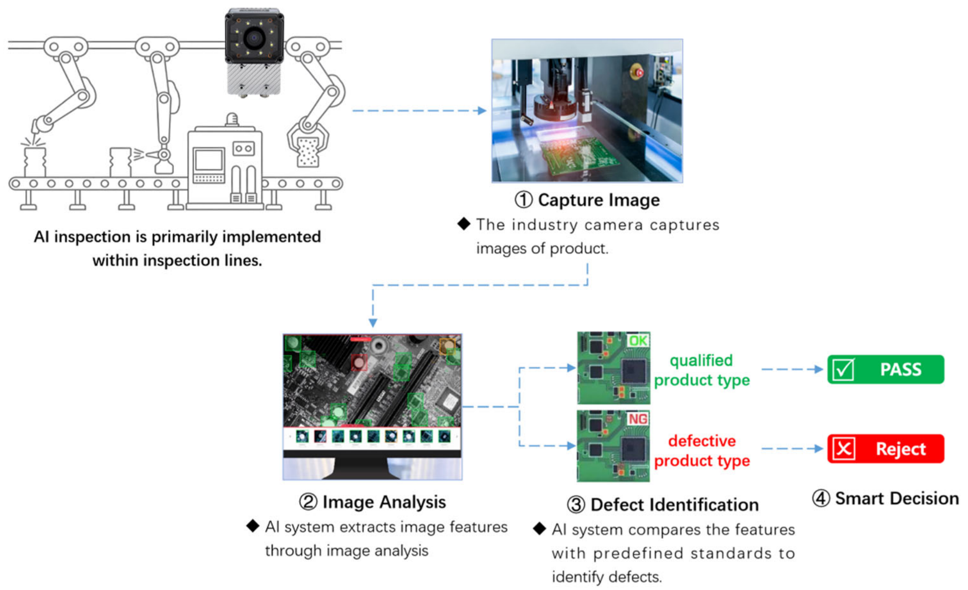

FIGURE 1 AI inspection process.

to study the operational strategies of supply chain members regarding the impacts of AI inspection on the supply chain in the quality management field.

The adoption of AI inspection has sparked a significant industry debate. Companies like HPE and Lenovo are at the forefront, leveraging AI to transform their inspection routines and enhance the efficiency of retail return (HPE, 2023; Instrumental, 2023). In contrast, entities such as Boeing maintain a cautious stance, preferring traditional methods over AI for quality inspection (Federal Aviation Administration, 2023). Given the divided opinion on adopting AI inspection for quality management, our research primarily addresses the question: *Should the manufacturer adopt AI inspection in supply chain quality management, especially when AI promises greater accuracy and lower costs than traditional methods?* While one might intuit, guided by previous findings (Li & Li, 2022), a straightforward endorsement of AI under these conditions, our investigation reveals that the decision to embrace AI inspection is not as clear-cut as it may appear.

Our results suggest that even if AI inspection performs well in enhancing inspection accuracy and reducing inspection costs, the manufacturer might not always adopt it. The counter-intuitive result stems from the possible drawbacks of AI technology, including the high operation costs from retail returns, which might exceed those of traditional systems. Companies need to weigh the accuracy of their suppliers' conventional inspection methods against the potential rise in retail operational costs, as well as technology-related expenses. Interestingly, our study also reveals that manufacturers might opt for AI inspection even when it is less accurate or more costly, highlighting the complexity of technology adoption decisions.

Our study extends the discussion beyond the manufacturer's decision to adopt AI inspection, to further consider the mutual decision-making on whether the manufacturer and supplier should pursue technology sharing. For instance, GE in the aviation sector utilizes AI inspection to enhance its own product quality but does not share the technology with its supplier (Bjerregaard, 2023), in contrast to HPE in the electrical sector, which adopts AI inspection internally and also extends this advanced technology to its supplier, Foxconn, promoting a cooperative quality management strategy (HPE, 2023). This leads to our second critical research question: *Should the manufacturer and supplier pursue the dual AI inspection strategy when the revenue from technology-sharing exceeds the setup costs?* Conventional wisdom suggests that companies favor technology-sharing when it promises significant revenue (Arora et al., 2013). However, our findings suggest that this is not always the case, and the manufacturer or supplier may still be reluctant to technology sharing even when the revenue from sharing is higher than the initial costs of technology setup.

The collaborative technology-sharing strategy may induce the manufacturer to adjust its investment in AI inspection technology as a measure of cost mitigation. Some manufacturers, such as printed circuit board (PCB) firms, may invest less in AI inspection to identify appearance defects. In contrast, others, like Toyota, may invest more to detect internal and external quality failures. Given this decision, we aim to address the third question: *Should the manufacturer invest more when sharing technology with the supplier in the supply chain?* Ge and Hu (2008) propose that the coordination relationship in the supply chain could lead to higher investment, promoting the quality level. However, we find that the manufacturer may invest less when sharing AI inspection technology with the supplier. Our result suggests that with stronger technical capabilities and lower initial costs of technology setup, manufacturers should strategically reduce their investment for better performance of technology-sharing.

The adoption of AI technology in the supply chain may generate spillover effects. Hence, our study analyzes the impact of AI inspection from the supplier's perspective, posing this question: *Does AI inspection adoption benefit the supplier?* Although Reyniers and Tapiero (1995) find that the practical and cost-efficient inspection policies by manufacturer benefit the supplier, our findings show that regardless of whether AI inspection is solely conducted by the manufacturer or shared with the supplier, both approaches may still pose risks to the supplier's interests. Therefore, we recommend that suppliers carefully evaluate the decision on AI inspection technology, taking into account specific factors like the defect rate of the product and the efficacy of traditional inspection methods.

While AI holds promise for enhancing efficiency and reducing reliance on human labor, a recent report shows that excessive AI automation cannot adapt to the changes in complex factory work, which may increase the supply chain burden (Büchel & Floreano, 2018; Hou et al., 2024). This can, paradoxically, add to the challenges faced by supply chains. Similarly, Kumar et al. (2020) critiques the over-enthusiasm for new supply chain management technologies, noting that the hype often leads to unrealistic expectations and subsequent disappointment. This leads to another interesting research question: *Is AI inspection universally beneficial for the supply chain?* Contrary to the optimism expressed by Bai et al. (2022), who suggest that technology innovation can amplify the positive impact of quality investment along the supply chain, our results show that adopting AI inspection may not always reduce the overall costs.

The rest of the article is structured as follows. Section 2 reviews the related literature. Section 3 presents our model. Section 4 summarizes the results. Section 5 provides discussion and managerial insights. We consider several model extensions and analyze the robustness of our results in Section 6. Finally, we conclude this study by providing executive and policy implications in Section 7.

2 | LITERATURE REVIEW

Our work is related to the following three streams of literature: inspection strategy, supply chain quality management, and new technology in quality management. In this section, we summarize the research context and highlight our contributions. For clarity, we illustrate our research context and contributions in Figure EC.1 in the Appendix.

2.1 | Inspection strategy

Most studies in this stream examine how firms utilize inspection to identify whether products meet quality standards and to analyze the impacts of these inspection practices on both product quality and retail pricing strategies (Chen et al., 2022; Reyniers & Tapiero, 1995). Further, some studies investigate the relationship between the inspection strategy and technology investment in quality or inspection (Erkoc et al., 2023; Lee & Li, 2018). Our research is similar to these in its focus on the manufacturer's optimal inspection strategies but is unique in its consideration of advanced technology like AI inspection technology on manufacturers' choice of inspection modes.

Although the existing research on inspection strategy considers technology investment in quality inspection, attention has mainly been given to cases where the firm invests in inspection by training the inspector or increasing the number of test runs. In addition, because plenty of firms concentrate on the concrete implementation of AI inspection technology, the academic studies within this research stream are mostly technical, not managerial (Azamfirei et al., 2023). As a result, the operations management literature lacks a concentration on AI inspection strategy, a gap that our study fills by considering inspection modes to investigate the impacts of AI technology on manufacturer inspection strategies. Interestingly, we find that AI inspection technology is not always helpful.

The research on inspection strategies examines firms' choices whether to inspect or not, and their decisions on inspection level if they do so (Chen et al., 2022; Kim et al., 2022). Furthermore, some studies refine the inspection level consideration to encompass inspection accuracy or sampling ratio. For example, Lee & Li (2018) consider the buyer's investment decision in inspection accuracy for incoming products from the supplier with full inspection. Similar to Erkoc et al. (2023), our model sets AI inspection accuracy as a variable determined by the manufacturer's technology investment. However, differing from these studies in the way they consider, our research considers implementation practices for AI technology as a means to promote full inspection. Additionally, given the characteristics of the technology reducing the need for human resources, we incorporate the negative correlation between the unit inspection cost and technology investment in our model extension. Our study contributes to the literature by investigating the manufacturer's investment decisions regarding AI inspection accuracy to assist the managers in adjusting technology investment to achieve higher supply chain operations efficiency.

2.2 | Supply chain quality management

Supply chain quality management is a systematic approach that engages key stakeholders to enhance the overall performance of the supply chain, focusing on product quality and cost efficiency of logistics and retail. Many studies investigate firms' various product quality strategies to improve supply chain performance within decentralized and centralized supply chains (Fu et al., 2020). Some studies analyze the impact of quality risk ratings or vendor certification on the supplier's quality improvement (Hwang et al., 2006; Zhou & Johnson, 2014). Other scholars put effort into identifying the roles of supplier and manufacturer in supply chain quality management (Dong et al., 2016; Shen & Sun, 2023), going further

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to examine the effects of the supplier-manufacturer relationship on retail efficiency. Similar to these studies, our research focuses on the supplier-manufacturer relationships in supply chain quality management, examining the manufacturer's and supplier's quality decisions in a collaborative supply chain.

The literature also explores various quality contracts between suppliers and manufacturers to optimize cost efficiency across all stages of the supply chain. In one related study, Dong et al. (2016) compare an inspection-based approach to an external failure-based approach in outsourcing supply chains, suggesting that inspection effectively reduces agency costs by preventing retail returns. Chakraborty et al. (2019) focus on collaborative quality strategies in a supply chain involving two competing manufacturers, evaluating the economic return on three cost-sharing mechanisms. Zhang et al. (2022) study the decisions of the contract manufacturer regarding product quality and design incentive contracts under two outsourcing structures, while Bondareva and Pinker (2019) propose a buyer-supplier dynamic contract where the buyer leverages inspection and compensation contracts to induce the supplier's quality investment. Yet, few studies jointly explore the impact of the collaborative inspections involving the supplier and manufacturer on cost optimization in the supply chain. However, quality inspection is a cost-effective method for identifying and preventing quality issues, thereby reducing operational costs in the supply chain (Jonble, 2023). Hence, the study on the gap in the impact of collaborative inspection is necessary. To fill this gap, our study model investigates a two-level inspection process and then quantifies its impact on supply chain performance.

The literature on the manufacturer-supplier collaboration mainly analyzes the situations where manufacturers invest in supplier quality improvement through technical and financial support (Agrawal et al., 2016). However, our study differs from this stream of literature. In our work, we follow the practical case of HPE and explore a new collaborative relationship where the manufacturer shares new inspection technology with the supplier. To guide manufacturers and suppliers in leveraging AI inspection technology better, we analyze the impact of technology-sharing on supply chain quality management. Our work complements the literature by showing the downside of technology-sharing. We find that technology-sharing may not always benefit the supply chain members.

2.3 | New technology in quality management

Prior research indicates that new technologies, like the Internet of Things, AI, and blockchain, create value in quality management by supporting production, distribution, and retail stages of the supply chain (Choi et al., 2022). Moreover, some studies provide insights on the adoption of new technology in different manufacturing sectors from a technology perspective (Olsen & Tomlin, 2020), while others investigate technology innovations in quality management with an empirical approach (Cui et al., 2022; Senoner et al., 2022). Our study is similar to these studies, though focusing on both the advantages and disadvantages of adopting AI technology in quality management, with a particular focus on optimizing retail returns.

Although the literature considers the adoption of AI in different fields of quality management, such as retail and production, there is an absence of research into how AI inspection technology can reshape quality management and improve cost efficiency. Additionally, some studies emphasize the advantages of technology innovation for quality management, including higher quality levels, lower human costs, and more accurate analysis capabilities (Kumar et al., 2020). However, these studies often overlook the potential disadvantages of new technology. To fill this gap, our study focuses on adopting AI in inspection and helps managers develop AI-driven supply chain quality management. Our work sets the parameter of AI inspection accuracy as a variable to emphasize the relationship between technical input and output of AI inspection.

Following the model setup of Senoner et al. (2022), who investigate the impacts of technology investment on production and retail activities, we consider the manufacturer's decision on technology innovation in the inspection process conducted by the upstream supplier and downstream manufacturer. Moreover, some studies examine the effects of advanced technology on redesigning business processes, suggesting that advanced technology overcomes the defects in traditional trade-offs (Cui et al., 2022). Similarly, we analyze the new trade-offs driven by AI inspection. We also propose new dual strategies in AI-driven supply chain quality management, examining the effects of AI inspection from a cost-reduction perspective. Interestingly, our study indicates that adopting AI in quality inspection may prove detrimental.

3 | THE MODEL

In this section, we introduce the model setup, with key notations summarized in the Appendix (Section EC.1). Based on the diverse practices of AI inspection adoption across various industries, our study focuses on inspection-oriented quality management in a supply chain comprising a manufacturer (denoted with subscript m) and a supplier (denoted with subscript s), with a two-stage process illustrated in Figure 2. For the convenience of exposition, we define the supplier's quality inspection as *Stage 1* and the manufacturer's quality inspection as *Stage 2*, occurring before the retail phase.

3.1 | Supplier's quality inspection

In *Stage 1*, upon receiving the manufacturer's product order, the supplier produces N units of products and then inspects them to ensure their reliability (Hsieh & Liu, 2010). Product reliability is reflected in the defect rate of products, denoted by $p \in [0, 1]$, with a higher p reflecting lower product reli-

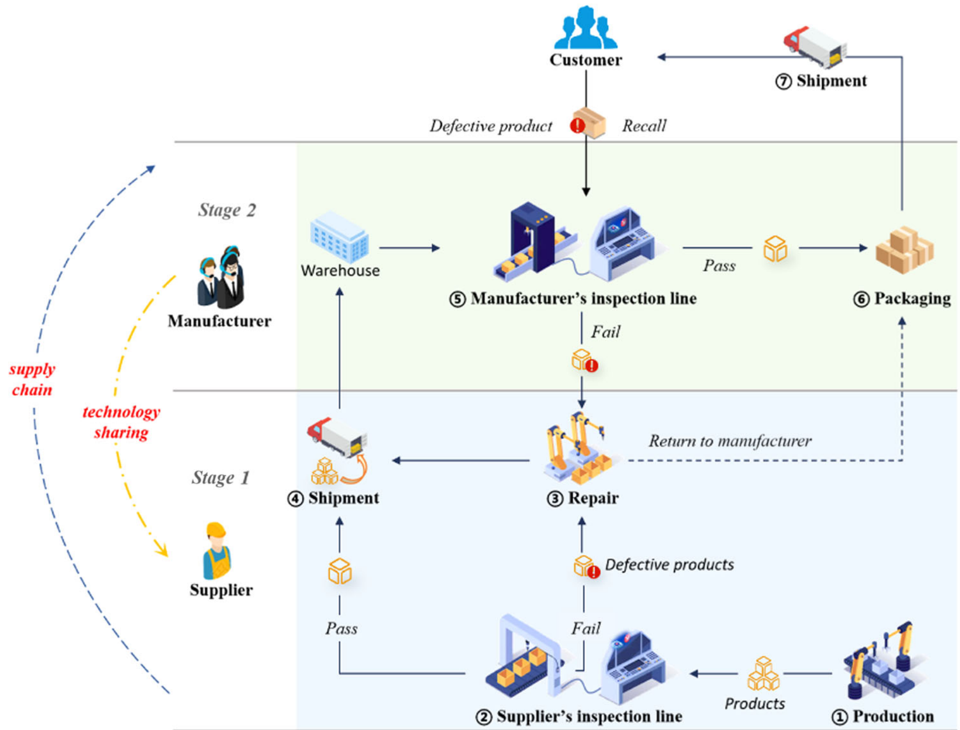

FIGURE 2 The quality inspection process in a supply chain.

ability (Gao et al., 2023). Generally, firms adopt traditional inspection to control product quality. However, some suppliers have recently cooperated with manufacturers to acquire AI inspection capabilities. Consequently, the supplier implements either traditional inspection (denoted with subscript t) or AI inspection (denoted with subscript a), depending on the manufacturer's decision about whether to share technology with the supplier and the supplier's decisions about whether to accept it. As such, unless both the manufacturer shares technology and the supplier accepts it, the supplier will adopt traditional inspection.

When adopting the traditional inspection method to identify defective products, the supplier bears internal costs, including inspection and repair costs. In traditional inspection mode, firms like Boeing typically opt for sample inspection due to high inspection costs and lengthy check time (Cavanaugh, 2023; Federal Aviation Administration, 2023). Following this practice, the supplier pays inspection costs $N\theta_s c_t$ for inspection operations, where $\theta_s \in (0,1)$ is the supplier's sampling ratio and c_t is the corresponding per-unit inspection cost. Notably, the inspection is imperfect in identifying all product defects, conditional on inspection accuracy (Dong et al., 2016). If the supplier's traditional inspection accuracy is $\alpha_s \in (0,1)$, then it can correctly inspect $Np\theta_s\alpha_s$ defective products, leading to a reduction in the defect rate from p to $p(1-\theta_s\alpha_s)$. When these faulty products are rejected during the inspection, the supplier repairs them and incurs costs $Np\theta_s\alpha_s r$, where r is the per-unit repair cost.

When accepting technology sharing, the supplier, following Lenovo's practice, can employ AI inspection to improve inspection efficiency, particularly in full inspection and reduced unit inspection cost (Instrumental, 2023). Specifically, AI inspection technology enables firms to inspect products at a lower per-unit cost of AI inspection, c_a, where $c_a < c_t$; that is, inspection costs change from $N\theta_s c_t$ to Nc_a. Moreover, the supplier's inspection accuracy is consistent with the manufacturer's AI inspection accuracy x, so the supplier can identify and repair Npx flawed items. In this technology-sharing transaction, the manufacturer is responsible for configuring the AI technology, in return for which the supplier pays the manufacturer a fixed technology-sharing fee F for accessing (Intel, 2023). Additionally, because AI inspection involves some high-precision equipment, the supplier incurs an up-front setup cost of u for the installation and necessary equipment. After the inspection, the supplier ships the batch of products, including those repaired, to the downstream manufacturer.

3.2 | Manufacturer's quality inspection

In *Stage 2*, the manufacturer conducts an inspection of the received products before packaging them (Kim et al., 2022). When the manufacturer adopts traditional inspection, it undertakes inspection costs $N\theta_m c_t$, where θ_m is the manufacturer's sampling ratio. The manufacturer's ability to identify defective products depends on the sampling ratio and inspection accuracy. Given the manufacturer's inspection accuracy α_m, the manufacturer can recognize $Np(1-\theta_s\alpha_s)\theta_m\alpha_m$ defective items. If the product is rejected during

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the inspection, the supplier repairs the defect and then returns the qualified product back to the manufacturer, leading to a unit repair cost r and unit logistics cost L_s (Erkoc et al., 2023).

The manufacturer can invest in AI technology to establish a completely automated inspection process. Due to the adoption of full inspection, inspection costs become Nc_a, where c_a is the unit cost of AI inspection. In practice, as the accuracy of AI inspection increases, the manufacturer's investment in AI inspection technology also increases (Bondareva & Pinker, 2019). To reflect the effects of diminishing marginal return, the investment is usually modeled as a convex increasing function of the technology's inspection accuracy (Lee & Li, 2018; Zhang et al., 2021). Given AI inspection accuracy $x \in (0, 1)$, the manufacturer incurs a technology investment $\frac{1}{2}\lambda x^2 + u$ and identifies $Np(1 - \theta_s\alpha_s)x$ units of defective products. Parameter λ represents the efficiency of converting technology investment into inspection accuracy, and parameter u denotes the up-front step cost stemming from the equipment of AI inspection.

To further enhance the quality of the supply chain, the manufacturer can share technology with the supplier through embedding an AI inspection system and equipment into the supplier's existing IT infrastructure. When the supplier agrees to adopt this shared technology, due to the need for system compatibility and retraining, the manufacturer must undertake considerable efforts toward the technology configuration, including remote data transmission and system standardization (LandingAI, 2020; Li & Chen, 2012). A higher AI inspection accuracy x requires more extensive efforts to configure AI inspection (Intel, 2023) successfully. Hence, the manufacturer incurs a configuration cost kx to ensure consistent quality management, and the supplier's AI inspection accuracy becomes x. The parameter k acts as the configuration cost coefficient, and a lower value of k means a stronger manufacturer's capability of technology configuration. In the sharing environment, the manufacturer discovers $Np(1 - x)x$ units of defective products during its inspection process.

Following the retail release, once the batch of products, including repaired items, reaches consumers, any defects are identified through usage, potentially triggering retail returns (Zhang et al., 2022). Referring to the example of retail returns by Sanyo and Lenovo (MacMillan, 2007), the manufacturer faces a unit logistic cost L_m to retrieve each defective product from customers, while the supplier incurs L_s for each retail returned item from the manufacturer (Geda et al., 2023). When a return occurs, the supplier and the manufacturer share a unit external failure cost E, encompassing expenses such as settlements of lawsuits and public notifications (Kim et al., 2022). Specifically, the manufacturer bears βE, and the supplier covers $(1 - \beta)E$, reflecting their respective shares of the external failure cost, where $\beta \in [0, 1]$. The supplier is generally accountable for the defective products regardless of whether these flaws are discovered by the manufacturer or customers (Sabouri et al., 2015). Consequently, the supplier bears the overall repair cost Npr.

3.3 | Timeline

Given the strategic options available to firms in practice, this study considers three distinct schemes: (i) Traditional Inspection (TI)—both the manufacturer and supplier rely on conventional inspection methods, without adopting AI technology; (ii) Sole AI Inspection (SA)—the manufacturer invests in AI inspection technology, while the supplier continues with traditional methods; (iii) Dual AI Inspection (DA)—the manufacturer invests in and shares AI inspection technology, and the supplier accesses it. Next, we illustrate the timing of the model, which is also illustrated in Figure 3.

(1) The manufacturer makes two decisions regarding quality management: Whether to invest in AI inspection technology and, if so, whether to share it with the supplier. Then, the supplier decides whether to access technology if the manufacturer shares technology.
(2) The manufacturer determines the level of investment in the AI inspection technology (i.e., $\frac{1}{2}\lambda x^2 + u$).
(3) The event sequence faced by the manufacturer and supplier is as follows:
  (a) Under a TI scheme, the manufacturer and supplier adopt traditional inspection with accuracy α_m, α_s, and a unit cost of traditional inspection c_t. The supplier needs to repair defective items with a unit repair cost r, and when the manufacturer returns the faulty products for repairs, the supplier incurs a unit logistics cost L_s and repair cost r. During the retail stage, when end customers return faulty items, the manufacturer incurs a unit logistic cost L_m, as both the manufacturer and the supplier also suffer the external failure costs at βE and $(1 - \beta)E$, respectively, due to retail return of the defective products.
  (b) Under an SA scheme, the supplier adopts traditional inspection with accuracy α_m and a unit cost of traditional inspection c_t. The supplier also needs to repair defective items with a unit repair cost r, while the manufacturer adopts AI inspection with accuracy x and a unit cost of AI inspection c_a. When the manufacturer returns the defective products, the supplier incurs a unit logistics cost L_s. During the retail stage, when end consumers return faulty items, the manufacturer incurs a unit logistic cost L_m. Additionally, the manufacturer and the supplier bear the external failure costs at βE and $(1 - \beta)E$, respectively.
  (c) Under a DA scheme, both the supplier and manufacturer adopt AI inspection with accuracy x and a unit cost of AI inspection c_a. The supplier also needs to repair defective items with a unit repair cost r. The manufacturer is charged for a technology configuration cost kx and, in turn, charges the supplier a technology-sharing fee F. When the manufacturer returns the defective products, the supplier incurs a

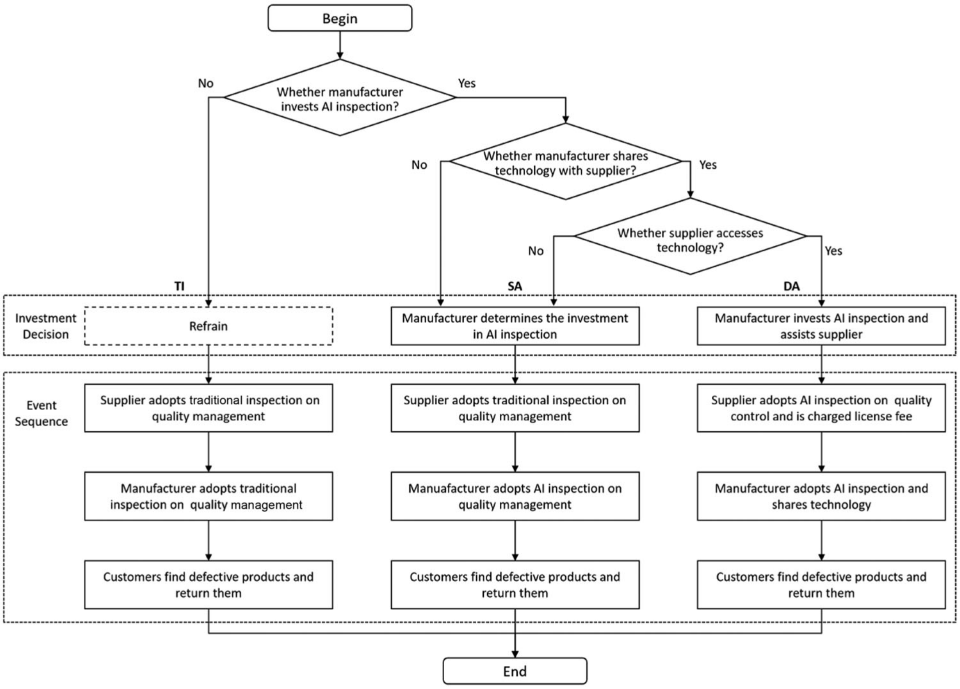

FIGURE 3 Model timeline.

unit logistics cost L_s, and then when end customers return faulty items during the retail stage, the manufacturer incurs a unit logistics cost L_m. Due to the product return losses, the manufacturer and the supplier bear external failure costs at βE and $(1-\beta)E$, respectively.

4 | RESULTS

In this section, we establish the total cost functions for the manufacturer and supplier under three scheme options: TI, SA, and DA. We solve the game equilibrium and provide the relevant results and analytical proofs in the Appendix (Section EC.3).

Under the TI scheme, the manufacturer opts for manual inspection without extra investment. The manufacturer's total cost equals the sum of its inspection costs, logistic costs, and external failure costs, while, in addition to these costs, the supplier also bears the additional burden of repair costs. Under the SA scheme option, in comparison, the manufacturer invests in AI technology for a more economical unit cost of inspection, whereas the supplier's total cost is similar to that in the TI case. Under the DA scheme, the manufacturer allows the supplier to access AI technology, improving quality inspection efficiency across the supply chain. Unlike the SA scheme, collaborative use of AI inspection technology leads to potential improvement in the supplier's inspection accuracy, with the resulting decrease in product quality failure rate benefiting the manufacturer and the supplier. In this case, the manufacturer may also enjoy lower total costs from the revenue earned from sharing its technology, as the supplier's total cost rises with the sharing fees it pays for the improved quality inspection.

We use the binary variable $1_a \in \{0,1\}$ to denote the manufacturer's decision whether to invest in AI inspection technology, whereby $1_a = 0$ indicates that the manufacturer doesn't invest, and $1_a = 1$ indicates that the manufacturer invests. Similarly, another binary variable $1_M \in \{0,1\}$ indicates the manufacturer's decision to share technology, and $1_S \in \{0,1\}$ indicates the supplier's decision to access the technology. When $1_a = 1$ is satisfied, if the manufacturer chooses $1_M = 0$ or the supplier chooses $1_S = 0$, then the manufacturer does not share technology or the supplier does not access technology. If the manufacturer decides $1_M = 1$ and the supplier chooses $1_S = 1$, then the manufacturer is willing to share technology, and the supplier accesses it. Therefore, the manufacturer's total cost function is simplified as follows:

$$
\begin{aligned}
C_m(1_a, 1_M, x) = {} & N[(1-1_a)\theta_m c_t \\
& +1_a c_a] + Np[1-(1-1_a 1_M 1_S)\theta_s \alpha_s - 1_a 1_M 1_S x][1 \\
& -(1-1_a)\theta_m \alpha_m - 1_a x](L_m + \beta E) \\
& +1_a(\frac{1}{2}\lambda x^2 + u) + 1_a 1_M 1_S (kx - F).
\end{aligned}
$$

The supplier's total cost function is given as:

$$
\begin{aligned}
C_s(1_S) = {} & N[(1-1_a 1_M 1_S)\theta_s c_t + 1_a 1_M 1_S c_a] \\
& +Npr + Np[1-(1-1_a 1_M 1_S)\theta_s \alpha_s - 1_a 1_M 1_S x][1-(1 \\
& -1_a)\theta_m \alpha_m - 1_a x](1-\beta)E + Np[1-(1-1_a 1_M 1_S)\theta_s \alpha_s
\end{aligned}
$$

$-1_a 1_M 1_S x]L_s + 1_a 1_M 1_S(F+u).$

The supply chain's total cost function is given as: $C = C_m(1_a, 1_M, x) + C_s(1_S)$.

To minimize total costs, the manufacturer strategically chooses 1_a, 1_M, and x, while the supplier determines 1_S. By backward induction, we first solve the total equilibrium costs of the manufacturer and supplier under the TI, SA, and DA schemes, which are summarized in our Lemmas. We then prove the existence of a Nash equilibrium and provide the equilibrium conditions of the best scheme, as shown in Lemma 1.

Lemma 1. *The manufacturer's optimal scheme is summarized as follows:*

(a) If $c_a > c_{a11}$ and $c_a > c_{a12}$, then the manufacturer attains the lowest total cost under the TI scheme;
(b) If $F < F_{11}$ and $c_a < c_{a11}$, then the manufacturer attains the lowest total cost under the SA scheme with its optimal AI inspection effort level $x = \frac{(1-\theta_s\alpha_s)Np(L_m+\beta E)}{\lambda}$;
(c) If $F > F_{11}$ and $c_a < c_{a12}$, then the manufacturer attains the lowest total cost under the DA scheme with its optimal AI inspection effort level $x = \frac{2Np(L_m+\beta E)-k}{2Np(L_m+\beta E)+\lambda}$.

The expressions of the above thresholds c_{a11}, c_{a12}, and F_{11} are shown in the Appendix (Section EC.2).

The above results demonstrate that the manufacturer tends to invest more when incurring a higher unit external failure cost (i.e., higher βE), and invest less when the cost coefficient of AI technology is relatively high (i.e., higher λ), aligning with previous research (Erkoc et al., 2023). Moreover, we observe that there is diminishing sensitivity toward AI inspection efforts to mitigate external losses under the DA scheme, while the sensitivity drops to the point of insignificance under the SA scheme (i.e., $\frac{d^2x^{DA}}{d(L_m+\beta E)^2} < 0$ and $\frac{d^2x^{SA}}{d(L_m+\beta E)^2} = 0$). This trend occurs because the changes in the magnitude of AI inspection efforts more significantly affect the failure rate of the end products, leading to a reduction in retail return costs under DA. Hence, when the manufacturer bears a higher share of the external failure cost, the variation in AI inspection effort diminishes. This result emphasizes that manufacturers who face substantial retail return costs do not always blindly pursue technology innovation within a collaborative environment.

5 | DISCUSSION AND MANAGERIAL INSIGHTS

In this section, we address the research questions raised in Section 1.2 and present the findings. The proofs of the propositions are provided in the Appendix (Section EC.5). We also conduct numerical experiments to examine the rationality of our results and visually represent it in the Appendix (Section EC.4).

5.1 | Should the manufacturer adopt AI inspection in the supply chain?

Manufacturers have utilized AI inspection to prevent defective products from entering the retail market, such as Toyota in the automotive industry and Weichai in the automotive engine industry (Weichai, 2019). However, some manufacturers still insist on traditional inspection. For instance, in the aviation industry, Boeing adopts manual and visual methods to inspect the dimensions of products. Hence, manufacturers are debating whether to adopt AI inspection as an alternative to traditional inspection in supply chain quality management (Cavanaugh, 2023). To understand the manufacturer's decision to choose AI inspection strategies (i.e., $1_a = 1$), we address our first question in Proposition 1: *Should the manufacturer adopt AI inspection in supply chain quality management, especially when AI promises greater accuracy and lower costs than traditional methods?* Additionally, we address another critical question: *Should the manufacturer refuse AI inspection in the supply chain quality management, especially when AI lags behind traditional methods in accuracy or inspection costs?*

Proposition 1.

(a) Even if AI inspection accuracy is higher than traditional inspection (i.e., $x^{SA} > \alpha_m$ and $x^{DA} > \alpha_m$) and the AI inspection cost is lower (i.e., $c_a < \theta_m c_t$), the manufacturer may not adopt AI inspection. Interestingly, this happens when the supplier's traditional inspection accuracy is in a given immediate range (i.e., $\max\{\alpha_{s1}, \alpha_{s3}\} < \alpha_s < \alpha_{s2}$).
(b) Even if AI inspection accuracy is lower than traditional inspection (i.e., $x^{SA} < \alpha_m$ or $x^{DA} < \alpha_m$) or the AI inspection cost is higher (i.e., $c_a > \theta_m c_t$), the manufacturer may still adopt AI inspection. Interestingly, this happens when the supplier's traditional inspection accuracy is higher than a given threshold (i.e., $\alpha_s > \alpha_{s2}$) or lower than a given threshold (i.e., $\alpha_s < \max\{\alpha_{s1}, \alpha_{s3}\}$).

The expressions of the above thresholds α_{s1}, α_{s2}, and α_{s3} are $\alpha_{s1} = \frac{1}{\theta_s} - \frac{\sqrt{2\lambda[N(c_a-\theta_m c_t)+u]+\lambda^2\theta_m^2\cdot\alpha_m^2}+\lambda\theta_m\alpha_m}{Np(L_m+\beta E)\theta_s}$, $\alpha_{s2} = \frac{1}{\theta_s} - \frac{-\sqrt{2\lambda[N(c_a-\theta_m c_t)+u]+\lambda^2\theta_m^2\cdot\alpha_m^2}+\lambda\theta_m\alpha_m}{Np(L_m+\beta E)\theta_s}$, *and* $\alpha_{s3} = \frac{1}{\theta_s} - \frac{N(c_a-\theta_m c_t)-F+u}{\theta_s Np(L_m+\beta E)(1-\theta_m\alpha_m)} - \frac{4Np(L_m+\beta E)k+2Np(L_m+\beta E)\lambda-k^2}{2\theta_s Np(L_m+\beta E)(2Np(L_m+\beta E)+\lambda)(1-\theta_m\alpha_m)}$.

Senoner et al. (2022) suggest that most firms adopt AI technology in quality management intending to enhance inspection accuracy and mitigate the high costs associated with labor, with industry leader Intel boasting that AI inspection consistently outperforms human visual inspection in terms of product surface and appearance assessments (Intel, 2023). Because of this stellar performance, semiconductor companies have embraced AI technology for quality inspection purposes, although the limited capability of AI inspection in complex equipment industries has led to a relatively low adoption rate among enterprises (GrandViewResearch, 2021). Based on these practices, one may intuit that the manufacturer's decision to adopt AI inspection depends on its efficiency regarding inspection accuracy and costs. However, interestingly, our findings show that even if AI inspection is more efficient (i.e., higher inspection accuracy and lower inspection costs), the manufacturer may not always choose to implement it in the supply chain.

The result of Proposition 1 can be explained as follows: Higher AI inspection accuracy has a positive impact on reducing the product defect rate (i.e., $\frac{dp(1-\alpha_s\theta_s)(1-x)}{dx} < 0$ and $\frac{dp(1-x)(1-x)}{dx} < 0$). Because fewer defective products enter the market, the manufacturer's external losses caused by retail returns (e.g., logistic and external failure costs) decrease (i.e., lower $Np(1-\alpha_s\theta_s)(1-x)(L_m+\beta E)$ and $Np(1-x)^2(L_m+\beta E)$). However, in some cases, even with AI inspection, the external losses from defective products may decrease insignificantly or even increase, failing to compensate for AI technology expense. This is because the final product defect rate depends on the supplier and manufacturer's inspections. The supplier's higher inspection accuracy could prevent excessive final product defect rate and external losses, whereas higher AI inspection accuracy may save limited retail return costs but requires the manufacturer to pay more AI technology expense (i.e., higher $\frac{1}{2}\lambda x^2$). Thus, despite the cost advantages of AI inspection (i.e., $c_a < \theta_m c_t$), the benefits derived from the reduced external losses may not necessarily compensate for the increased AI technology expense.

Figure EC.2 in the Appendix visually demonstrates the relationship between the manufacturer's total cost and the supplier's traditional inspection accuracy. When the supplier's traditional inspection accuracy is in a given immediate range (i.e., $\max\{\alpha_{s1}, \alpha_{s3}\} < \alpha_s < \alpha_{s2}$), the benefits of AI inspection, such as lower external losses and lower inspection costs, could be insignificant, which cannot compensate for the high AI technology expense. Thus, the manufacturer would not adopt AI inspection. Conversely, when the supplier's traditional inspection accuracy is higher than a given threshold (i.e., $\alpha_s > \alpha_{s2}$), the manufacturer has no need for higher AI inspection accuracy. In this case, although the positive effect of AI inspection on reducing external losses could be slight or even negative, the AI technology expense is much lower. The lower inspection costs can offset the increased AI technology expense and external losses. Thus, the manufacturer would adopt AI inspection. Additionally, when the supplier's traditional inspection accuracy is lower than a given threshold (i.e., $\alpha_s < \max\{\alpha_{s1}, \alpha_{s3}\}$), the manufacturer could benefit even more from reduced external losses through higher AI inspection accuracy and the cost savings outweigh the AI technology expense. Hence, the manufacturer would benefit more from AI inspection. Moreover, as shown from the threshold functions, the unit AI inspection cost decreases the value of thresholds α_{s1} and α_{s3}, but increases the value of threshold α_{s2} (i.e., $\frac{d\alpha_{s1}}{dc_a} < 0$, $\frac{d\alpha_{s3}}{dc_a} < 0$, and $\frac{d\alpha_{s2}}{dc_a} > 0$), which means that the manufacturer is more willing to adopt AI inspection with lower unit AI inspection cost.

The result provides a practical implication for manufacturers who dominate the technology investment in supply chain quality management. Even when the AI inspection accuracy is both more accurate and less expensive than traditional inspection, the manufacturer may not see a drop in its quality management costs with AI inspection, aligning with the findings of Lee & Li (2018). Specifically, if the supplier's traditional inspection accuracy is in a given intermediate range, the manufacturer's savings in external losses and inspection costs cannot offset AI technology expenses. Managers should consider the trade-offs between external failure costs and AI technology expenses, as well as the impact of the supplier's inspection accuracy. Our result suggests that if the supplier's traditional inspection accuracy is in the given immediate range, the manufacturer (e.g., General Motors) should not adopt AI inspection as a supply chain management tool. However, if the manufacturer insists on AI inspection strategy under these circumstances, managers should reduce the unit AI inspection cost to ease the conditions for successful AI inspection adoption, making AI inspection a more cost-effective strategy. Conversely, if the supplier's traditional inspection accuracy is relatively low or high, the manufacturer (e.g., Tesla) should adopt AI inspection.

To illustrate that our results can hold in practice, we can look to the anecdotal evidence of Toyota's strategic change to embrace AI inspection. In 2010, Toyota encountered a series of retail return incidents stemming from faulty accelerator pedals supplied by supplier CTS. This return incident revealed several shortcomings in Toyota's supplier audits for safety-critical products, such as lower inspection accuracy and the sampling rate of suppliers (Evans, 2010). In response, Toyota adopted AI inspection in the quality management process and intensified its quality audits on key suppliers (Reuters, 2020), illustrating how a supplier's diminished inspection accuracy with traditional methods can prompt the manufacturer to prefer AI inspection.

This result contributes to the relevant literature in supply chain quality management with a focus on inspection strategy. As shown in Sections 2.1 and 2.2, although the literature has explored how manufacturers leverage traditional inspection strategy to manage supply chain quality for maximizing the profit, these studies have not considered the adoption of AI inspection in a supply chain. Moreover, as shown in Section 2.3, the literature on AI inspection mainly concentrates on technology adoption and presents systematic reviews of the current technology trends (Azamfirei et al., 2023; Cui et al., 2022). In response, this study explores the impact of AI inspection strategy on quality management and proposes a framework for manufacturers to determine whether to adopt AI inspection.

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5.2 | Should the manufacturer and supplier pursue dual AI inspection strategy?

The manufacturer's adoption of AI inspection technology in a supply chain raises a new question: Should the manufacturer share technology and the supplier access it? In the electronic information industry, HPE, a global leader in AI inspection, provides AI inspection technology to strategic supplier partners, such as Foxconn, for cooperation and integration of quality management (HPE, 2023). However, in the aviation industry, GE and its suppliers refuse to share AI inspection technology (Bjerregaard, 2023). The decision to choose the dual AI inspection strategy (i.e., $1_M = 1$ and $1_s = 1$) has sparked a heated discussion. Motivated by a lack of clear direction in this discussion, we attempt to analyze the critical question: *Should the manufacturer refuse to share AI inspection technology or its supplier refuse to accept technology when the revenue from technology-sharing exceeds the configuration cost?* We also figure out another vital question: *Should the manufacturer share AI inspection technology and its supplier access technology when the revenue from technology-sharing is less than the configuration cost?*

Proposition 2.

(a) *Even if the manufacturer's revenue from the technology-sharing fee is higher than the configuration cost (i.e., $F > kx^{DA}$), the manufacturer and the supplier would opt for the SA strategy when the supplier's traditional inspection accuracy is higher than the given threshold (i.e., $\alpha_s > min\{\alpha_{s4}, \alpha_{s5}\}$).*
(b) *Even if the manufacturer's revenue from the technology-sharing fee is less than the configuration cost (i.e., $F < kx^{DA}$), the manufacturer and supplier would still prefer the DA strategy when the supplier's traditional inspection accuracy is lower than the given threshold (i.e., $\alpha_s < min\{\alpha_{s4}, \alpha_{s5}\}$).*

The expressions of the above thresholds α_{s4} and α_{s5} are: $\alpha_{s4} = \frac{1}{\theta_s} - \frac{\lambda}{\theta_s NpL_m} + \frac{1}{\theta_s NpL_m}\sqrt{2\lambda\left[\frac{\lambda}{2} + F - \frac{4NpL_m k + 2NpL_m\lambda - k^2}{2(2NpL_m + \lambda)}\right]}$ *and* $\alpha_{s5} = \frac{1}{\theta_s} - \frac{L_s}{2(1-\beta)ENp(L_m+\beta E)\theta_s} + \frac{1}{\theta_s}\{\frac{1}{N^2p^2(1-\beta)E(L_m+\beta E)}\{Np(1-\beta)E[\frac{\lambda+k}{2Np(L_m+\beta E)+\lambda} + \frac{NpL_s}{2Np(1-\beta)E}]^2 + \frac{L_s^2 - L_s(L_m+\beta E)}{4(1-\beta)E(L_m+\beta E)} + Np(1-\beta)E + u + F + N(c_a - \theta_s c_t)\}\}^{\frac{1}{2}}$.

Arora et al. (2013) suggest that technology companies favor deals where the technology licensing revenue is higher, and so it follows that if the manufacturer's technology-sharing revenue from the supplier is higher than the configuration cost, the manufacturer prefers to share AI inspection technology. However, Proposition 2 shows a counter-intuitive result that even if the manufacturer's technology-sharing revenue exceeds the configuration cost, the manufacturer may not share technology, or the supplier refuses to access technology. Conversely, even if the manufacturer's technology-sharing revenue is lower than the configuration cost, the manufacturer may still decide to share technology, and the supplier accesses technology.

The explanation for the result of Proposition 2 is as follows. According to Proposition 1, in the SA scenario, when the supplier's inspection accuracy is higher, leading to a substantial decline in external losses, the manufacturer invests less in AI inspection (i.e., $\frac{dx^{SA}}{d\alpha_s} < 0$). However, in the DA environment, because the supplier also conducts AI inspection, the supplier's traditional inspection accuracy does not affect AI technology expense (i.e., $\frac{dx^{DA}}{d\alpha_s} = 0$). Note that with technology-sharing, the supplier's inspection accuracy is the same as that of the manufacturer. To significantly reduce retail return costs associated with defects, the manufacturer needs to invest more to achieve a higher level of overall quality inspection. In this case, the manufacturer incurs higher AI technology expense and configuration costs, which may decrease its profitability, while the supplier's lower inspection accuracy induces the manufacturer to invest more in the SA environment. Hence, by sharing technology, the manufacturer can achieve the same level of overall quality inspection with lower AI technology expenses and configuration costs. Moreover, the supplier's lower inspection accuracy amplifies the positive impact of AI inspection on reducing external losses. Therefore, even with configuration cost and technology-sharing fee, the supplier can attain superior quality inspection capability by accessing technology provided by the manufacturer.

When the manufacturer and supplier adopt the DA scheme rather than the SA scheme, if the supplier's traditional inspection accuracy is higher than a given threshold (i.e., $\alpha_s > \alpha_{s4}$), the manufacturer needs to attain higher AI inspection accuracy. In this case, the improvement in AI technology expense and configuration cost outweighs the technology-sharing revenue. Hence, technology-sharing aggravates the manufacturer's cost burden so that the manufacturer would refuse to share technology with the supplier. Additionally, Figure EC.3 in the Appendix shows how the supplier's total cost changes with α_s. If the supplier's traditional inspection accuracy exceeds a given threshold (i.e., $\alpha_s > \alpha_{s5}$), the reduction in external losses from AI inspection may be slight, which cannot offset technology-sharing fee and configuration cost. Therefore, the supplier may refuse to access technology. On the other hand, when the supplier's traditional inspection accuracy is lower than a given threshold (i.e., $\alpha_s < min\{\alpha_{s4}, \alpha_{s5}\}$), the manufacturer could keep the same level of overall quality inspection with the lower technology expense, while the supplier can achieve a significant enhancement in quality. With more effective return of technology expense, the manufacturer and supplier are inclined to the DA strategy.

The result provides an important takeaway: When only the manufacturer adopts AI inspection, the lower traditional inspection accuracy of the supplier motivates the manufacturer to set a higher AI inspection accuracy. However, when both the supplier and manufacturer adopt AI inspection, this motivation disappears, and the supplier processes the same AI inspection capability as that of the manufacturer, as is consistent with Lee & Li (2018) and Liu et al. (2018). Although the manufacturer earns from sharing fees and the supplier contends with the costs, the lower AI inspection accuracy increases defective products, causing a dilemma where the manufacturer profits amidst losses and the supplier bears more external losses. Hence, firms should reconsider how the cost trade-off is affected by the supplier's traditional inspection accuracy, rather than focusing on the profitability of the technology-sharing business.

Our result may provide a plausible explanation for Lenovo's choice of DA strategy and GE's choice of SA strategy (Bjerregaard, 2023; Instrumental, 2023). Most electronic manufacturers who operate in complex supply chains, such as Lenovo, may face suppliers with lower accuracy of manual quality inspection, like Sanyo. Because Sanyo's manual quality inspection failed to find battery issues, Lenovo suffered great losses and chose to provide technical support to these suppliers (MacMillan, 2007). Sharing AI inspection technology helps Lenovo improve the overall quality management of the supply chain, compensating for the suppliers' losses caused by limited manual inspection capabilities and enhancing product quality. In contrast, in the aviation industry, where suppliers generally have higher levels of manual quality inspection, with rigorous quality control systems, GE Aviation focuses on developing its own AI inspection technology to meet high standards and ensure product reliability.

The result of Proposition 2 contributes to the existing research regarding collaborative quality management involving technology-sharing. As summarized in Sections 2.2 and 2.3, although some studies focus on the manufacturer's technical support to the supplier in the product development stage (Lee & Li, 2018), the existing research has not considered technology-sharing strategy in supply chain quality inspection. Moreover, few studies focus on manufacturers' investment strategies in collaborative quality management. Therefore, our study provides guidelines to the manufacturer on the decision to share technology and the supplier on the decision to access technology.

5.3 | Should the manufacturer invest more in technology sharing?

After identifying the decision on technology-sharing, it is critical to explore whether the manufacturer invests more or less in AI inspection technology. In supply chain quality management involving the collaboration of the manufacturer and supplier, the DA scheme option not only allows the manufacturer to provide technical support to the supplier but also to benefit from technology-sharing revenue. Because technology-sharing may cause effort distortion and spillover effects, the manufacturer needs to adjust technology investment to minimize the quality cost (Bapna et al., 2023; Im et al., 2019). Some manufacturers, like HPE, invest more to achieve a higher quality in a DA environment (HPE, 2023). However, due to the IT infrastructure and environment limitations, sharing AI inspection technology in the supply chain could result in complex cost performance trade-offs, which makes some manufacturers hesitate to invest more (Intel, 2023). Thus, we propose the following question: *Should the manufacturer always invest more when sharing AI inspection with the supplier in the supply chain?*

Proposition 3. *When the manufacturer adopts AI inspection and shares the related technology with the supplier, it may invest less in technology. This occurs when the coefficient of the configuration cost is relatively high (i.e., $k > k_1$) or the capability of AI inspection is relatively high (i.e., $\lambda < \lambda_1$).*

As previously stated, the manufacturer, as a leader, tends to exert more effort in improving the supplier's product quality and enhancing the overall efficiency of the supply chain (Lee et al., 2020). In our study, with the benefits of technology-sharing, one may intuit that a DA strategy would further encourage the manufacturer to invest more in collaborative quality management of the supply chain. However, Proposition 3 challenges this intuition by demonstrating that the manufacturer's technology investment may decrease with technology-sharing.

The explanation for the result of Proposition 3 is as follows. When the manufacturer shares AI inspection technology with the supplier, the higher coefficient of the configuration cost induces the manufacturer to invest less in the DA scheme (i.e., $\frac{dx^{DA}}{dk} < 0$). If the coefficient of the configuration cost is relatively high (i.e., $k > k_1$), then the technology investment is lower in DA than that in SA (i.e., $x^{DA} < x^{SA}$). Moreover, when the capability of AI inspection is higher (i.e., lower λ), the manufacturer sets a higher AI inspection effort (i.e., $\frac{dx^{SA}}{d\lambda} > 0$ and $\frac{dx^{DA}}{d\lambda} > 0$) in the SA and DA schemes. Because both the supplier and manufacturer use AI inspection, the DA scheme could achieve a more significant marginal cost reduction in external losses compared with SA (i.e., $(1-\theta_s\alpha_s)(1-x^{SA}) > (1-x^{DA})^2$). In this case, the manufacturer obtains more benefits from AI inspection. Hence, when the capability of AI inspection is relatively high (i.e., $\lambda < \lambda_1$), the manufacturer invests less in DA than in SA (i.e., $x^{DA} < x^{SA}$).

Proposition 3 yields crucial insights for managers that technology-sharing does not necessarily prompt the manufacturer to boost its investment to optimize the performance of AI technology in the collaborative supply chain, similar to the results of Demirezen et al. (2020) and Zhu et al. (2007). Managers should observe that the flexibility of technology-sharing in supply chain quality inspection enables the stronger positive effects of AI inspection, especially when the manufacturer's configuration cost or technical capability is higher. Our result suggests that when the coefficient of configuration cost is relatively low, the manufacturer (e.g.,

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Ford) with advantageous technical capabilities can strategically reduce AI inspection efforts during the sharing scenario. By technically supporting the supplier, the manufacturer can benefit from overall quality enhancement, reducing the total cost.

Our findings may plausibly support Intel's transformation in AI inspection technology investment. As a leader in the supply chain, Intel has strong capability in leveraging AI technology to identify defects of wafers and packaging (Intel, 2024). In 2023, Intel collaborated with the supplier, ASRock, to achieve complete automated PCB inspections upstream and downstream of the supply chain (Intel, 2023). This initiative resulted in a notable 258% improvement in inspection efficiency, with an accuracy of 97%. Although this collaboration yielded promising results, Intel did not invest further in this collaborative project.

As shown in Sections 2.1 and 2.2, the literature mainly analyzes the impact of related factors, such as suppliers' traditional inspection accuracy on manufacturers' AI inspection efforts; few studies investigate the manufacturer's investment decisions under different AI inspection strategies in the supply chain. Our study demonstrates that the manufacturer's lessened investment sometimes creates more value through sharing technology with the supplier. Furthermore, our findings indicate that the manufacturer with lower technical capability can adjust the investment to optimize the overall quality management cost under the SA and DA schemes.

5.4 | Does AI inspection adoption always benefit the supplier?

With AI inspection adopted upstream in the supply chain, suppliers may benefit from the free-ride effect (Wang et al., 2023). Moreover, McKinsey's survey reveals that suppliers can benefit from the technical collaboration projects initiated by manufacturers, as the suppliers can gain cutting-edge technology access without shouldering the entire financial burden of technology research (Gutierrez et al., 2020). However, as AI inspection tools become more costly, suppliers may suffer the financial burden, potentially impacting their competitiveness in the market (Shilov, 2021). Thus, while AI inspection offers potential benefits, it also introduces uncertainties and financial pressures for suppliers. Motivated by the debate on the supplier's status with AI inspection, we attempt to analyze the key question: *Does the AI inspection adoption always benefit the supplier?*

Proposition 4.

(a) When the manufacturer adopts a sole AI inspection strategy, the supplier's cost would be higher (i.e., $C_s^{SA} > C_s^{TI}$) than that in traditional inspection strategy if the defect rate is relatively low (i.e., $p < p_1$).

(b) When the manufacturer shares AI inspection technology, if the supplier's traditional inspection accuracy is relatively high (i.e., $\alpha_s > \alpha_{s6}$), then the supplier's cost would be higher than that in traditional inspection strategy (i.e., $C_s^{DA} > C_s^{TI}$).

When the manufacturer adopts a practical and highly cost-effective inspection policy, the supplier can save more on costs (Reyniers & Tapiero, 1995), so it follows that if the manufacturer adopts AI inspection, the supplier, as a collaborator in supply chain quality management, could benefit from technology innovation. However, Proposition 4 suggests that this is not always the case, and AI inspection adoption may not consistently yield cost advantages for the supplier.

The explanation of Proposition 4 is as follows. In the SA scheme, the lower product defect rate induces the manufacturer to set a lower AI inspection accuracy (i.e., $\frac{dx^{SA}}{dp} > 0$). With a lower AI inspection accuracy, the decrease in defective products may be less significant than in traditional inspection (i.e., lower $Np(1-\theta_s\alpha_s)x^{SA}$). If the defect rate is lower than a given threshold (i.e., $p < p_1$), then the supplier suffers greater losses from defects; that is, AI inspection aggravates the supplier's total cost. According to Proposition 2, in the DA scheme, the higher supplier's inspection accuracy weakens the positive impact of AI inspection on reducing external losses (i.e., lower $(1-x^{DA})^2$). If the supplier's inspection accuracy is higher than a given threshold (i.e., $\alpha_s > \alpha_{s6}$), it saves less on retail returns or even incurs more external losses. Consequently, although the DA scheme offers cost advantages over the SA scheme, the supplier may still incur higher total costs than under the TI scheme.

The result implies that the supplier should anticipate potential detriments from the manufacturer-driven technical innovation, which aligns with the existing literature (Chakraborty et al., 2019; Lee & Li, 2018; Wang et al., 2023). The supplier may benefit from technology innovation, but these advancements may also pose the challenges of increased quality management costs, contingent upon factors such as the supplier's traditional inspection effort and the reduction in unit inspection costs. Our result may plausibly help explain why the collaboration between HPE and Foxconn in AI inspection ended. The DA action helps HPE streamline inspection processes and reduce expenses but may aggravate the financial burden of Foxcoon, thereby prompting Foxconn to embark on its own AI technology research (Foxconn, 2021).

The findings of Proposition 4 contribute to the literature regarding technology innovation in supply chain quality management. As summarized in Section 2.2, the literature focuses on exploring the impact of manufacturers' R&D innovation on other supply chain members, ignoring the perspective of technology innovation in quality inspection (Zhang et al., 2022). Additionally, some studies on inspection investment fail to consider collaborative technology adoption, where the supplier gains access to technology through the manufacturer's technology sharing (Chen et al., 2022; Zhu et al., 2007). Therefore, to fill this gap, our research analyzes the promoting effect of technology innovation on the supplier under technology sharing and nonsharing scenarios. Our results help suppliers recognize the benefits of AI inspection, seize opportunities for mutual success, and mitigate potential risks associated with cost shifting.

5.5 | Is AI inspection universally beneficial for the supply chain?

The manufacturer's technology investment has a significant impact on suppliers, which reversely affects the total cost of the supply chain. As leaders in the supply chain, manufacturers often prioritize utilizing cutting-edge technologies to achieve next-level performance in supply-chain management (Gutierrez et al., 2020). Consequently, some major companies, like Lenovo, have invested in AI inspection with the ultimate goal of optimizing the supply chain cost. However, the report of Tesla shows that AI may not eliminate supply chain issues, adversely hindering cost optimization within the supply chain (Büchel & Floreano, 2018). Hence, the debate of whether AI inspection benefits the supply chain has not yielded a clear conclusion. To address this debate, we attempt to analyze the key question: *Is AI inspection universally beneficial for the supply chain?*

Proposition 5. *When the manufacturer chooses the sole AI inspection strategy in the supply chain, the total costs for the supply chain would be lower than that with traditional inspection (i.e., $C^{SA} < C^{TI}$) if and only if the external failure cost shared by the manufacturer is higher (i.e., $\beta > \beta_1$).*

Huang et al. (2023) suggest that supply chain collaboration and IT advancement positively influence supply chain resilience, leading to cost savings within the supply chain. Moreover, the report by McKinsey uses examples and data to show AI improved inspection accuracy and costs, which seems beneficial for the supply chain (Bauer et al., 2017). Therefore, it would seem that technical innovation is an effective method to optimize the quality management cost of the supply chain. Consistent with this intuition, in our model, the DA scheme performs better for the supply chain than the TI scheme (i.e., $C^{DA} < C^{TI}$). However, the result of Proposition 5 contradicts this intuition. Adopting the SA scheme does not always yield positive outcomes for the supply chain.

The result of Proposition 5 can be explained as follows. A higher external failure cost shared by the manufacturer leads to greater AI inspection accuracy (i.e., $\frac{dx^{SA}}{d\beta} > 0$). As the accuracy of AI inspection increases, there is an increasing marginal effect on reducing retail returns. Although the supply chain incurs a higher technology expense, reducing retail return costs is more significant. If the manufacturer incurs a relatively high proportion of the external failure cost (i.e., $\beta > \beta_1$), it would have more willingness to achieve higher AI inspection accuracy and avoid greater retail return costs (i.e., lower $Np(1-\theta_s)(1-x^{SA})(E+L_m)$). In this case, the reduction in retail return costs can offset the technology expense (i.e., $\frac{1}{2}\lambda x^2$), making AI inspection beneficial for the supply chain. Conversely, if the manufacturer takes on a relatively low proportion of the external failure cost (i.e., $\beta < \beta_1$), the incentive to invest in AI inspection diminishes. Consequently, the meager benefits from reducing retail return costs fail to offset the technology expense, leading to a less favorable outcome for the entire supply chain.

Policymakers should note that adopting AI inspection may harm the supply chain if the manufacturer bears a lower proportion of the external failure cost. Although AI has been touted as a universal solution for supply chain management issues, managers should recognize the complexities in cost trade-offs, similar to the findings of Huang et al. (2023) and Li & Li (2022). When manufacturers shoulder the higher external failure cost, they can identify more defects and save more inspection costs, creating higher value in the supply chain. In contrast, if they bear a lower cost, the savings from retail returns and inspection costs may not compensate for the technology expenses. With this in mind, policymakers should actively promote AI inspection adoption in the automotive industry to alleviate the demand for costly experienced inspectors, as insufficient inspections contribute to high retail return incidents (Cavanaugh, 2023). Our findings may help explain why the government nurtures AI inspection technology in the automotive industry, aiming to enhance product quality (Briefs, 2023).

The result of Proposition 5 analyzes the impact of AI inspection on the supply chain. As discussed in Section 2.2, although the literature has extensively explored emerging technologies in supply chain management, few studies examine the impact of adopting AI inspection on management efficiency (Li & Li, 2022). Moreover, as shown in Section 2.3, most studies have employed empirical methods to analyze the impact of technology innovation on the supply chain (Mithas et al., 2022). To expand the scope and methodology in supply chain management, our study uses a game-theoretic approach to investigate the consequences of AI inspection in different manufacturing decision-making scenarios. Our findings provide valuable insights and practical recommendations for managers and policymakers in optimizing supply chain quality inspection operations.

6 | MODEL EXTENSIONS

In this section, we extend our base model in two different directions. To begin with, we focus on an extended setting where the unit inspection cost is related to the AI inspection effort. Subsequently, we incorporate false positive inspection into the model, considering that a qualified product can be misidentified as defective. We illustrate that our findings from the main model are robust to these alternative model settings.

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6.1 | Unit inspection cost relying on the AI inspection effort

With AI inspection technology, firms can automatically inspect each product with a lower unit inspection cost (Erkoc et al., 2023). Hence, in the main model, we consider that the unit cost of AI inspection c_a is lower than that of traditional inspection c_t (i.e., $c_a < c_t$). However, according to the report of Bauer et al. (2017), the higher inspection accuracy of AI technology reduces the need for labor and resources during the inspection process, resulting in more cost savings in the unit inspection cost. In this sense, as AI technology expense increases, the unit inspection cost presents a downward trend. As a result, we consider that the unit inspection cost is related to the AI inspection effort in this subsection. That is, the unit inspection cost is defined as $(1 - x)c_t$ rather than c_a, aligning with Liu et al. (2023). We examine the robustness of Propositions 1–5 from the main model and provide the corresponding Propositions EC.1–EC.5 in the Appendix.

Proposition EC.1, similar to Proposition 1, indicates that even if AI inspection accuracy is higher than traditional inspection accuracy (i.e., $x^{SA} > \alpha_m$ and $x^{DA} > \alpha_m$), the manufacturer may not adopt AI inspection. Moreover, Proposition EC.3 reveals that with the higher unit cost of traditional inspection, the manufacturer invests less in the DA scheme than in SA, because higher traditional inspection costs lead to larger marginal reductions in inspection costs and external losses under DA. In this scenario, the manufacturer must consider the trade-offs between cost reduction and configuration cost and should thus invest less. The results of Propositions EC.2-EC.5 are qualitatively the same as the results of Propositions 2–5. For example, Proposition EC.2 shows that even if the revenue from technology-sharing is lower than the configuration cost (i.e., $F < kx^{DA}$), the manufacturer and supplier would still prefer dual AI inspection when the supplier's traditional inspection accuracy is lower than the given threshold (i.e., $\alpha < \alpha_{S4}$).

6.2 | False-positive inspection

Aligned with existing literature (Sabouri et al., 2015), we assume that AI inspection technology identifies each qualified product with minimal error, thus excluding false positives from our main analysis. This premise holds substantial validity across various sectors; however, the automotive industry presents a notable exception. Here, AI-driven inspections may incur false positives, leading to the unnecessary rejection of acceptable products and escalating waste and costs (LandingAI, 2020). Consequently, this subsection introduces a nuanced consideration of false positives, which creates a gap between the effort put into AI inspection and the actual accuracy achieved. Specifically, with a false-positive probability denoted as b, the manufacturer's investment in AI inspection effort, x, yields an actual inspection accuracy, a, where $x = a + \Delta\alpha$ and $\Delta\alpha = \frac{1-p}{p}b$. Here, $\Delta\alpha$ represents the bias introduced by the probability of false positives. We examine the robustness of Propositions 1–5 from the main model and provide Propositions EC.6–EC.10 in the Appendix.

The results of Propositions EC.6–EC.10 are qualitatively the same as the results of Propositions 1–5. For example, Proposition EC.6 shows that manufacturers may hesitate to adopt AI inspection, despite its superior accuracy over traditional methods (i.e., $x^{SA} > \alpha_m$ and $x^{DA} > \alpha_m$) when the supplier's traditional inspection accuracy falls within a certain intermediate range (i.e., $\max\{\alpha_{s21}, \alpha_{s23}\} < \alpha_s < \alpha_{s22}$). Furthermore, Proposition EC.8 demonstrates that with low false positive rates (i.e., $b < b_1$), manufacturers might prefer lower investments in the DA scheme compared to SA. This preference stems from the DA scheme's enhanced actual accuracy due to lower false positive rates, thereby reducing the influx of defective products into the manufacturer's inspection process and enabling cost reductions. Additionally, Proposition EC.9 indicates that adopting AI inspection, even when it yields higher accuracy than traditional methods (i.e., $x^{SA} - \Delta\alpha > \theta_m\alpha_m$), can adversely affect the supplier. This adverse effect is attributed to the supplier incurring higher retail return costs due to false positive inspections via AI technology, which might exceed the benefits of reduced retail returns.

7 | CONCLUSION

Emerging AI technology provides firms with a new tool for supply chain quality management. Manufacturers can utilize AI inspection in their quality inspection process as a substitute for traditional inspection (e.g., Toyota), and share AI technology with suppliers to further improve quality management (e.g., HPE). Based on these practical examples, our study analyzes a manufacturer's strategy to adopt AI inspection technology and the choice of whether to share technology with the supplier. This study is among the first to focus on a manufacturer's decision for the AI-driven inspection modes in a two-stage inspection process, helping firms and policymakers take advantage of AI's formidable capabilities.

7.1 | Managerial and policy implications

Our work provides implications for firms and policymakers aiming to manage quality collaboratively. According to Proposition 1, if the upstream supplier's traditional inspection accuracy is either very high or very low, the downstream manufacturer can benefit from adopting AI inspection. We demonstrate that the supplier's relatively high traditional inspection accuracy induces the manufacturer to adopt AI inspection, leading to an internal transformation of quality management costs between the manufacturer and supplier. In contrast, the supplier's relatively low traditional inspection accuracy incentivizes the manufacturer to adopt AI inspection to alleviate the burden of retail returns. For companies like General Motors, where the supplier's inspection accuracy does not fall into these extremes, our study suggests that adopting AI inspection may not be necessary.

We then explore the optimal collaboration strategy in supply chain quality management. Proposition 2 establishes that when the supplier's traditional inspection accuracy is lower than a given threshold, it is optimal for the manufacturer to share AI inspection technology with the supplier. The reason is that under a technology-sharing strategy, the manufacturer can improve the supplier's inspection capability to decrease retail returns, irrespective of whether the technology revenue is higher than the configuration cost. This result suggests that manufacturers like Apple should share AI inspections with suppliers like Foxconn when their suppliers' traditional inspection accuracy is relatively low. We also compare the manufacturer's technology investments under different collaboration strategies. Proposition 3 demonstrates that when choosing a technology-sharing strategy, the manufacturer may invest less than that without sharing technology, similar to the finding of Zhu et al. (2007).

Proposition 4 implies a key managerial insight that the supplier may be hurt when the manufacturer adopts AI inspection. Our result shows that when the manufacturer adopts sole AI inspection, the supplier can free-ride on the cost optimization if and only if the defect rate is relatively high. Our result also highlights that technology-sharing may harm the supplier when the supplier's traditional inspection accuracy is relatively high. Hence, we suggest that the supplier (e.g., Foxconn) should take action in response to the manufacturer's technology-sharing when AI cannot decrease the inspection cost.

Our findings also shed light on how the government could regulate AI inspection adoption. Proposition 5 illustrates how greater AI inspection may harm the supply chain under the SA strategy. In addition, when the manufacturer and supplier adopt AI inspection, the higher unit external failure cost may also harm the supply chain. Hence, we suggest that the government encourage automobile manufacturers to adopt AI inspection, and then go further by issuing regulations to prevent AI inspection from increasing the cost burden in light industries.

7.2 | Theoretical implication and future research directions

This work contributes to three primary research streams: inspection strategy, supply chain quality management, and new technology in quality management, providing new directions for the literature on inspection strategy. The literature often explores the impact of a firm's strategy on product quality or pricing decisions (Erkoc et al., 2023; Lee & Li, 2018), whereas we concentrate on the manufacturer's optimal inspection strategies and extend the research on supply chain quality management. While recent studies predominantly examine the roles of the supplier and manufacturer in the supply chain (Shen & Sun, 2023), we investigate how the collaboration between the supplier and manufacturer affects the manufacturer's decision on sharing AI inspection technology. This study also complements the research on new technology in quality management. Most papers have explored the impacts of new technology on various businesses from technology or empirical perspectives (Choi et al., 2022; Olsen & Tomlin, 2020; Tan, 2024), whereas we investigate the adoption of AI technology in quality management based on a game-theoretic model.

Our study has some limitations that create promising opportunities for future research. Firstly, although it is reasonable to assume that the manufacturer incurs a configuration cost to embed AI technology into the supplier's inspection process, our study does not account for the potential costs, such as technical consultation and maintenance fees. These cost factors could diminish the manufacturer's initiative to share technology. Secondly, by assuming a subordinate role for the supplier in the technology-sharing scenario, our analysis overlooks information asymmetry, where the supplier may not fully understand the utility of AI technology. Future research could investigate how the supplier navigates such uncertainty when making decisions on accessing the technology. Finally, it would be meaningful to explore the inspection strategy by incorporating multiple suppliers in the model, as their competition may impact technology innovation within the supply chain. We expect that the effects of competition could be amplified by the manufacturer's technology investment.

In summary, our work considers the interaction between the supplier and manufacturer in the inspection process and the effects of AI inspection, offering important implications for scholars, industry managers, and decision-makers and providing a novel perspective on quality management operations. By considering the operational characteristics of AI inspection and the collaboration between the supplier and the manufacturer, our work establishes a new model framework that incorporates the manufacturer's adoption of AI inspection and transformation of inspection modes. Our work provides a new perspective to research on quality inspection and supply chain management. Our results show that the manufacturer's decisions on the investment in AI inspection technology and subsequent operational strategy are critical in the supply chain. These results broaden the knowledge and theory for firms to promote AI inspection.

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REFERENCES

Agrawal, A., Kim, Y., Kwon, H.D. & Muthulingam, S. (2016) Investment in shared suppliers: Effect of learning, spillover, and competition. *Production and Operations Management*, 25(4), 736–750.

Arora, A., Fosfuri, A. & Rønde, T. (2013) Managing licensing in a market for technology. *Management Science*, 59(5), 1092–1106.

Azamfirei, V., Psarommatis, F. & Lagrosen, Y. (2023) Application of automation for in-line quality inspection, a zero-defect manufacturing approach. *Journal of Manufacturing Systems*, 67, 1–22.

Bai, C., Li, H.A. & Xiao, Y. (2022) Industry 4.0 technologies: Empirical impacts and decision framework. *Production and Operations Management*, Forthcoming.

Bapna, R., Gupta, A., Ray, G. & Singh, S. (2023) Single-sourcing vs. multisourcing: An empirical analysis of large information technology outsourcing arrangements. *Information Systems Research*, 34(3), 1109–1130.

Bauer, H., Richter, G., Wüllenweber, J., Breunig, M., Wee, D. & Klein, H. (2017) *Smartening up with Artificial Intelligence (AI)—What's in it for Germany and its Industrial Sector*. Digital McKinsey.

Bjerregaard, L. (2023) *GE, Waygate partner on AI-powered engine inspections*. Available at: https://aviationweek.com/mro/emerging-technologies/ge-waygate-partner-ai-powered-engine-inspections [Accessed 9th Nov 2024].

Bondareva, M. & Pinker, E. (2019) Dynamic relational contracts for quality enforcement in supply chains. *Management Science*, 65(3), 1305–1321.

Briefs, M. (2023) *Industrial system of testing equipment, little giants in niche markets and strategy for digital development*. Available at: https://merics.org/en/merics-briefs/industrial-system-testing-equipment-little-giants-niche-markets-strategy-digital [Accessed 9th Nov 2024].

Büchel, B. & Floreano, D. (2018) *Tesla's problem: Overestimating automation, underestimating humans*. Available at: https://theconversation.com/teslas-problem-overestimating-automation-underestimating-humans-95388 [Accessed 9th Nov 2024].

Business Research Insights (2023) *Automated industrial quality control market insights*. Available at: https://www.businessresearchinsights.com/market-reports/automated-industrial-quality-control-market-101319 [Accessed 9th Nov 2024].

BusinessDIT (2023) *AI in supply chain: Statistics, market, and future in 2023*. Available at: https://www.businessdit.com/ai-in-supply-chain [Accessed 9th Nov 2024].

Cavanaugh, C. (2023) *Inspection and quality control in manufacturing*. Available at: https://preprod.ptc.com/en/blogs/ar/inspection-and-quality-control-in-manufacturing [Accessed 9th Nov 2024].

Chakraborty, T., Chauhan, S.S. & Ouhimmou, M. (2019) Cost-sharing mechanism for product quality improvement in a supply chain under competition. *International Journal of Production Economics*, 208, 566–587.

Chen, J., Wei, H. & Xie, L. (2022) Mitigating product quality risk under external financial pressure: Inspection, insurance, and cash/collateralized loan. *Production and Operations Management*, 31(1), 304–317.

Choi, T.-M., Kumar, S., Yue, X. & Chan, H.-L. (2022) Disruptive technologies and operations management in the industry 4.0 era and beyond. *Production and Operations Management*, 31(1), 9–31.

Cui, R., Li, M. & Zhang, S. (2022) AI and procurement. *Manufacturing & Service Operations Management*, 24(2), 691–706.

Demirezen, E.M., Kumar, S. & Shetty, B. (2020) Two is better than one: A dynamic analysis of value co-creation. *Production and Operations Management*, 29(9), 2057–2076.

Dong, Y., Xu, K., Song, S. & Zhou, C. (2021) Quality reference in consumer product recalls. *Decision Sciences*, 52(4), 893–919.

Dong, Y., Xu, K., Xu, Y. & Wan, X. (2016) Quality management in multi-level supply chains with outsourced manufacturing. *Production and Operations Management*, 25(2), 290–305.

Erkoc, M., Gurnani, H., Ray, S. & Jin, M. (2023) Quality investment, inspection policy, and pricing decisions in a decentralized supply chain. *Production and Operations Management*, 32(1), 207–226.

Evans, S. (2010) *Toyota supplier audit finds 'misunderstanding' about quality control procedures*. Available at: https://www.motortrend.com/news/toyota-supplier-audit-finds-misunderstanding-about-quality-control-procedures-9032 [Accessed 9th Nov 2024].

Federal Aviation Administration (2023) *Airworthiness directives; the Boeing company airplanes*. Available at: https://www.federalregister.gov/documents/2023/07/10/2023-14330/airworthiness-directives-the-boeing-company-airplanes [Accessed 9th Nov 2024].

Foxconn (2021) *Foxconn announces FOXCONN NxVAE, unsupervised learning AI technology*. Available at: https://www.foxconn.com/en-us/press-center/events/csr-events/533 [Accessed 9th Nov 2024].

Fu, H., Li, K. & Fu, W. (2020) Investing in suppliers with capacity constraints in a decentralized assembly system. *Computers & Industrial Engineering*, 142, 106332.

Gao, Y., Johnson, N., Shen, B. & Tan, Y. (2023) Benefits of sourcing alternative inputs of manufacturers for suppliers. *Production and Operations Management*, 32(6), 1880–1894.

Ge, Z. & Hu, Q. (2008) Collaboration in R&D activities: Firm-specific decisions. *European Journal of Operational Research*, 185(2), 864–883.

Geda, A., Pu, J. & Qiu, L. (2023) The puzzle of online arbitrage and increased product returns: A game-theoretic analysis. *Production and Operations Management*, 32(8), 2387–2399.

Google Cloud (2021) *Google cloud industries: Artificial intelligence acceleration among manufacturers*. Available at: https://services.google.com/fh/files/blogs/google_cloud_manufacturing_report_2021.pdf [Accessed 9th Nov 2024].

GrandViewResearch (2021) *Surface vision and inspection market size, share & trends analysis report by components (hardware, software), by application (food & beverages, automotive, smart phones & tablets)*. Available at: https://www.grandviewresearch.com/industry-analysis/surface-vision-inspection-market [Accessed 9th Nov 2024].

Gutierrez, A., Kothari, A., Mazuera, C. & Schoenherr, T. (2020) *Taking supplier collaboration to the next level*. Available at: https://www.mckinsey.com/capabilities/operations/our-insights/taking-supplier-collaboration-to-the-next-level [Accessed 9th Nov 2024].

Hou, T., Li, M., Tan, Y. & Zhao, H. (2024) Physician adoption of AI assistant. *Manufacturing & Service Operations Management*, 26(5), 1639–1655.

HPE. (2023) *Making zero defects a reality—Relimetrics case study*. Available at: https://www.hpe.com/psnow/doc/a50003557enw.pdf?jumpid=in_pdfviewer-psnow [Accessed 9th Nov 2024].

Hsieh, C.-C. & Liu, Y.-T. (2010) Quality investment and inspection policy in a supplier–manufacturer supply chain. *European Journal of Operational Research*, 202(3), 717–729.

Huang, K., Wang, K., Lee, P.K. & Yeung, A.C. (2023) The impact of industry 4.0 on supply chain capability and supply chain resilience: A dynamic resource-based view. *International Journal of Production Economics*, 262, 108913.

Hwang, I., Radhakrishnan, S. & Su, L. (2006) Vendor certification and appraisal: Implications for supplier quality. *Management Science*, 52(10), 1472–1482.

Im, G., Rai, A. & Lambert, L.S. (2019) Governance and resource-sharing ambidexterity for generating relationship benefits in supply chain collaborations. *Decision Sciences*, 50(4), 656–693.

Instrumental. (2023) *Lenovo delivers approx. $1 unit savings and dramatically reduces rework using Instrumental*. Available at: https://instrumental.com/case-studies/lenovo-case-study [Accessed 9th Nov 2024].

Intel (2023) *Optimizing AI model training and refinement for automated optical inspection (AOI)*. Available at: https://geti.intel.com/case-study/optimizing-ai-model-training-and-refinement-for-automated-optical-inspection-aoi [Accessed 9th Nov 2024].

Intel (2024) *Intel launches world's first systems foundry designed for the AI era*. Available at: https://www.intel.com/content/www/us/en/newsroom/news/foundry-news-roadmaps-updates.html [Accessed 9th Nov 2024].

Jonble (2023) *Incoming quality control: What it is and why it's important*. Available at: https://www.jonble.com/blog/incoming-quality-control [Accessed 9th Nov 2024].

Kim, B., Koenigsberg, O. & Ofek, E. (2022) I don't "recall": The decision to delay innovation launch to avoid costly product failure. *Management Science*, 68(12), 8889–8908.

Kumar, A., Liu, R. & Shan, Z. (2020) Is blockchain a silver bullet for supply chain management? Technical challenges and research opportunities. *Decision Sciences*, 51(1), 8–37.

LandingAI (2020) *Redefining quality control with AI-powered visual inspection for manufacturing*. Available at: https://landing.ai/wp-content/uploads/2020/05/LandingAI_ManufacturingAIHurdles_Whitepaper_FINAL.pdf [Accessed 9th Nov 2024].

Lee, H.-H. & Li, C. (2018) Supplier quality management: Investment, inspection, and incentives. *Production and Operations Management*, 27(2), 304–322.

Lee, J., Krishnan, V. & Shin, H. (2020) Business models for technology-intensive supply chains. *Management Science*, 66(5), 2120–2139.

Li, M. & Li, T. (2022) AI automation and retailer regret in supply chains. *Production and Operations Management*, 31(1), 83–97.

Li, X. & Chen, Y. (2012) Corporate it standardization: Product compatibility, exclusive purchase commitment, and competition effects. *Information Systems Research*, 23(4), 1158–1174.

Liu, D., Tan, Y. & Mookerjee, V. (2018) When ignorance can be bliss: Organizational structure and coordination in electronic retailing. *Information Systems Research*, 29(1), 70–83.

Liu, G., Wang, H. & Shao, X. (2023) Technology investments into a supplier with upstream entry. *European Journal of Operational Research*, 305(1), 240–259.

MacMillan, R. (2007) *Lenovo recalls ThinkPad batteries made by Sanyo*. Available at: https://www.reuters.com/article/us-lenovo-recall-idUSN0130064720070301 [Accessed 9th Nov 2024].

Mithas, S., Chen, Z.-L., Saldanha, T.J. & De Oliveira Silveira, A. (2022) How will artificial intelligence and industry 4.0 emerging technologies transform operations management? *Production and Operations Management*, 31(12), 4475–4487.

Olsen, T.L. & Tomlin, B. (2020) Industry 4.0: Opportunities and challenges for operations management. *Manufacturing & Service Operations Management*, 22(1), 113–122.

Reuters. (2020) *Toyota, others look to AI as coronavirus challenges quality control practices*. Available at: https://europe.autonews.com/automakers/toyota-others-look-ai-coronavirus-challenges-quality-control-practices [Accessed 9th Nov 2024].

Reyniers, D.J. & Tapiero, C.S. (1995) The delivery and control of quality in supplier-producer contracts. *Management Science*, 41(10), 1581–1589.

Sabouri, A., Shechter, S.M. & Huh, W.T. (2015) Inspecting a vital component needed upon emergency. *Production and Operations Management*, 24(12), 1839–1851.

Senoner, J., Netland, T. & Feuerriegel, S. (2022) Using explainable artificial intelligence to improve process quality: Evidence from semiconductor manufacturing. *Management Science*, 68(8), 5704–5723.

Shen, Z.M. & Sun, Y. (2023) Strengthening supply chain resilience during COVID-19: A case study of jd.com. *Journal of Operations Management*, 69(3), 359–383.

Shilov, A. (2021) *AI meets chipmaking: Applied materialsincorporates AI in wafer inspection process*. Available at: https://www.anandtech.com/show/16565/applied-materials-wafer-inspection-tools-use-ai-and-big-data-to-cut-inspection-costs-by-3x [Accessed 9th Nov 2024].

Tan, Y. (2024) Implications of blockchain-powered marketplace of preowned virtual goods. *Production and Operations Management*, 33(6), 1393–1409.

Wang, J., Huang, T. & Lee, J. (2023) Cross-licensing in a supply chain with asymmetric manufacturers. *Manufacturing & Service Operations Management*, 25(5), 1623–1998.

Weichai (2019) *Tan Xuguang: The national-level quality inspection center built by Weichai needs to be world's first-class*. Available at: https://m.en.weichaipower.com/media_center/news/202109/t20210924_76522.html [Accessed 27th September 2019].

Zhang, M., Zhang, J., Sun, Y. & Cheng, T. (2022) How to outsource production considering quality management: Turnkey or buy-sell? *Omega*, 113, 102707.

Zhang, Z., Shivendu, S. & Wang, P. (2021) Is investment in data analytics always profitable? The case of third-party-online-promotion marketplace. *Production and Operations Management*, 30(7), 2321–2337.

Zhou, Z.Z. & Johnson, M.E. (2014) Quality risk ratings in global supply chains. *Production and Operations Management*, 23(12), 2152–2162.

Zhu, K., Zhang, R.Q. & Tsung, F. (2007) Pushing quality improvement along supply chains. *Management Science*, 53(3), 421–436.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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