The Application of AI in Optimizing Fresh Food Logistics Routes

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Abstract. The fresh food logistics industry is confronted with inherent challenges, which stem from the perishability of products, strict quality requirements, and increasingly fragmented and dynamic demand patterns. Traditional logistics models and optimization techniques often struggle in this high-risk environment, leading to low efficiency, high costs and significant food waste. This article explores the potential of artificial intelligence in addressing these key issues. Through a systematic literature review, the author comprehensively analyzed the application of artificial intelligence technology - including predictive analytics, intelligent path planning, computer vision, and autonomous systems - in the fresh food delivery model. Analysis shows that artificial intelligence technology can significantly enhance operational efficiency: dynamic path optimization can reduce transportation distance and fuel consumption, and predictive analysis can minimize inventory loss to the greatest extent. In addition, integrating AI-driven automation systems in warehouses can not only enhance processing speed but also reduce physical damage to goods. This article explores these findings in specific contexts and demonstrates that artificial intelligence is not only the key to coordinating the transformation of fresh food logistics and distribution, but also can enhance the resilience and sustainability of the supply chain. However, this field still faces challenges in terms of cost, data integration and regulation. The research ultimately indicates that artificial intelligence marks a paradigm shift in fresh food logistics, providing a powerful toolset for building a more efficient, flexible, and zero-waste supply chain system, and pointing out the key path for future research and practical application.

Keywords: Fresh food logistics, Supply chain, Perishability, Food waste, Artificial Intelligence, Predictive analytics, Intelligent routing.

1. Introduction

Path optimization is a core objective of logistics management and has a decisive impact on operational efficiency and cost structure. The emergence of artificial intelligence technology, including intelligent methods such as genetic algorithms, ant colony optimization algorithms and machine learning, has provided powerful tools for solving complex combinatorial optimization problems, thereby giving rise to more efficient and sustainable distribution solutions.

These challenges are particularly prominent in the logistics of fresh food - a field that not only has operational complexity but also imposes strict requirements on product integrity. The inherent perishable nature of fresh produce and food safety considerations require the supply chain to have strict traceability capabilities and continuous temperature control monitoring. Compared with traditional logistics, the traditional fresh food delivery model often suffers from significant inefficiency and astonishing loss rates. This contradiction has been intensifying under the evolution of consumption patterns and the transformation of retail formats: consumers have extremely high demands for quality, freshness and delivery timeliness. However, the dispersion and diversity of fresh produce sources have led to the gradual failure of large-scale centralized delivery models, which have been replaced by fragmented order structures characterized by small batches, high frequency and multiple temperature zones.

This paradigm shift has brought about unprecedented operational challenges: the complexity of path optimization has grown exponentially, and static planning algorithms are difficult to adapt to order fluctuations, dynamic road conditions, and real-time temperature control requirements. Cost control is becoming increasingly difficult, and the commodity loss rate and cold chain costs are constantly squeezing the profit margin. Stable quality assurance and user experience are hard to maintain. Any delay in any link may directly damage product quality and customer satisfaction.

It is precisely against this backdrop that artificial intelligence technology has demonstrated its transformative potential. By integrating and processing massive datasets - including historical orders, real-time GPS traffic conditions, weather forecasts, and inventory dynamics - artificial intelligence algorithms can build intelligent path planning models with predictive, simulation, and dynamic decision-making capabilities. This approach not only pursues optimal cost-efficiency trade-offs but also imbues the supply chain with unprecedented agility and resilience through precise demand forecasting and resource scheduling.

Consequently, this study aims to systematically investigate the application framework, key algorithms, and implementation efficacy of AI technologies in optimizing fresh food logistics routes.

By analyzing industry best practices (such as the innovative cases of leading enterprises like Hema Fresh), this article will explain how artificial intelligence specifically addresses the high dynamics and multiple constraints of fresh food logistics, and evaluate its role in enhancing operational efficiency, reducing product waste, and promoting sustainable development, thereby providing useful references for theoretical innovation and practical application in related fields.

2. Literature Review

This research involves two research fields: (1) fresh food logistics distribution models, (2) the application of artificial intelligence in logistics distribution, which are analyzed in this section.

2.1. fresh food logistics distribution models

The logistics and distribution of fresh food encompasses the organizational structures, operational processes, and network configurations established to facilitate the spatial and temporal transfer of perishable goods from production to consumption. Academic research in this domain focuses on delineating the distinctive characteristics of fresh food logistics that distinguish it from general goods logistics, and on systematically categorizing and evaluating prevailing distribution models.

As emphasized by Vilas-Boas, fresh food constitutes a specialized category within supply chains, characterized by inherent risks of perishability and contamination [1]. These distinctive attributes necessitates temperature-controlled environment, leading to the conceptualization of specialized logistics frameworks such as the cold chain [2], perishable food supply chain [3], or fresh food supply chain (FFSC) [4].

The operational challenges within this specialized chain are profound and multifaceted. Pal's analysis highlights that traditional logistics systems exhibit significant inefficiencies, largely due to insufficient coordination among logistics providers and complexities in optimizing vehicle allocation, which frequently results in suboptimal asset utilization and empty transportation [5]. For fresh products, such logistical inefficiencies are particularly critical, as delays directly translate into quality degradation, making efficiency improvement a formidable task. This inherent logistical inefficiency exists alongside the modern pressures noted by Shi, who emphasizes that under the dual impetus of smart city initiatives and the e-commerce wave, fresh food logistics has become an indispensable component of the modern supply chain. Within the complex network of production, circulation, and sales, a core and urgent issue is how to ensure the quality and safety of fresh produce while simultaneously achieving distribution efficiency [6].

In response to these challenges, scholars have dedicated efforts to classifying and analyzing the corresponding distribution models. Research on fresh product logistics originated earlier and achieved a more mature theoretical framework abroad compared to China. Consequently, domestic and international scholars often adopt distinct perspectives when examining distribution models. The mainstream models mentioned in the literature can directly address the issues of collaboration and efficiency raised by scholars such as Pal. They can mainly be classified into the following categories:

- Direct Distribution Model: This model involves shipping products directly from producers or central warehouses to retail stores or end-consumers. This model is often praised for its shorter lead time, which is crucial for maintaining the freshness of fresh produce. However, its cost-effectiveness and operational efficiency are highly dependent on order density and delivery distance.

- Warehouse-Centric Distribution Model: In this model, products are first consolidated at distribution centers before being dispatched. This move supports value-added services such as cross-warehouse operations, inventory management, and sorting and packaging. Although it will add an extra processing step, it is very likely to enhance loading efficiency and reduce transportation costs.
- Collaborative Distribution Model (or Common Distribution): This emerging model emphasizes resource-sharing among multiple suppliers or logistics providers to consolidate shipments. It is widely regarded as a direct response to the coordination failures identified by Pal and is a promising solution for reducing empty mileage, lowering overall logistics costs, and minimizing the environmental footprint of urban fresh food distribution.

2.2. The application of artificial intelligence in logistics distribution

The formidable challenges pervasive in fresh food logistics—specifically the imperative to enhanced efficiency, minimize waste, and ensure superior quality maintenance—are driving a paradigm shift towards intelligent, data-driven solutions. At the forefront of this transformation is Artificial Intelligence (AI), which is redefining logistics distribution through a suite of core technological applications. Its application scope is extensive, covering not only the estimation of demand and loss through predictive analysis, but also the optimization of resources through intelligent path planning, and further extending to the use of computer vision for quality control, as well as the realization of operational automation through autonomous systems.

2.2.1. Predictive analysis in Demand forecasting and Inventory management

Accurate demand forecasting constitutes the cornerstone of efficient logistics, a requirement that is particularly critical in the fresh food sector due to its minimal tolerance for error. This challenge is most pronounced at the retail level, where forecasting must achieve a delicate balance: generating highly disaggregated predictions at the individual product-store level while simultaneously synthesizing them into a coherent aggregate plan to guide upstream supply chain activities [7]. Moreover, the decentralized nature of retail introduces significant unpredictability, as localized promotional strategies and autonomous store-level decisions can create significant biases and errors in the forecast. The consequence of inaccurate forecasts extends beyond inventory issues, placing immense and direct strain on the entire downstream distribution network, including transportation capacity and route optimization plans [7]. It is precisely these inherent complexities that expose the limitations of traditional prediction methods and also provide sufficient reasons for adopting AI-driven solutions.

2.2.2. AI-Optimized Routing and Scheduling

To overcome the inefficiency of traditional logistics models, artificial intelligence algorithms are fundamentally reshaping the transportation planning system. These systems deeply integrate real-time and historical data - including traffic conditions, road infrastructure, meteorological information and vehicle performance parameters - to generate the optimal delivery routes and schedules that exceed those of ordinary GPS navigation. Artificial intelligence can perform multi-objective optimization, effectively reducing the risk of fresh food being exposed to adverse environments while minimizing driving distance, fuel consumption and delivery time. By dynamically reconfiguring vehicle routes in response to sudden delays, artificial intelligence effectively ensures that perishable goods sensitive to time can always be delivered to their destinations within the prescribed time window.

The implementation of these optimized routes is further augmented through robotics and automation at logistics nodes. Automated Guided Vehicles (AGVs) and mobile robots, recognized for their flexibility in path control capabilities, function as the physical executors of AI-generated operational schedules within warehouses and distribution centers [8]. Furthermore, the combination of robotics with sensors and imaging technologies provides critical real-time data [9], which can be fed back to the AI system to enable even more precise and adaptive dynamic routing, ensuring operational safety and efficiency.

This end-to-end intelligent capability is particularly crucial for promoting the resource sharing advocated by the collaborative distribution model. AI systems efficiently consolidate and optimize routing for goods originating from multiple suppliers, while automated physical systems guarantee the seamless execution of these complex logistical plans, creating a fully integrated and responsive distribution ecosystem.

2.2.3. Computer Vision for Quality Inspection and Handling

Ensuring food quality and safety has always been the core concern throughout the entire distribution chain. Computer vision systems based on artificial intelligence are being widely deployed to enhance the automation and precision of quality inspection processes.

The deployment of computer vision systems for quality inspection follows a standardized technical process, which includes five key links: image acquisition, preprocessing, image segmentation, feature extraction and classification [10].A critical component in this pipeline is the image acquisition phase, which utilizes specialized lighting configurations: front lighting is optimized for inspecting surface quality attributes such as color, texture, and skin defects, while back lighting improves the assessment of morphological attributes such as size and shape.

Building upon this technical foundation, vision systems installed at critical handling points—such as packaging facilities or warehouse entry points—can automatically identify defects, bruising, dimensional variations, color inconsistencies, and early indications of spoilage in fresh produce.

By training on large-scale image datasets, these systems have achieved detection throughput and consistency far exceeding the level of human intervention. Based on precise measurement results, automatic sorting and grading are achieved to ensure that only goods meeting specific quality standards can be delivered to the corresponding market channels, thereby effectively reducing downstream returns and losses.

In addition, the integration of computer vision technology facilitates the control of robots in automated warehousing environments, guiding mechanical arms to precisely handle fragile fresh products in the sorting and packaging process. This automated operation can significantly reduce physical damage and ensure the integrity of products throughout the logistics chain.

2.2.4. Autonomous Vehicles and Robots

The architecture of modern fresh food logistics is undergoing a fundamental transformation through the integration of autonomous vehicles and robotic systems. This shift is particularly evident in the evolution from traditional Automated Guided Vehicles (AGVs), which depend on centralized control for scheduling and path planning, to Autonomous Mobile Robots (AMRs) equipped with advanced hardware and control software capable of fully autonomous operation in dynamic environments. The distinguishing feature of AMRs lies in their decentralized decision-making capacity: these systems can independently communicate and negotiate with other operational assets, enabling the entire logistics network to respond with unprecedented agility to sudden changes in operational status and external conditions [11].

This technological evolution not only enhances the system's resilience and efficiency but also has a profound impact on traditional methods for logistics planning and control, establishing a critical technological foundation for building highly adaptive and intelligent fresh food logistics networks. In the field of fresh food logistics, warehouse automation is undergoing a profound transformation from traditional automated systems toward intelligent and flexible solutions. While conventional prove inadequate for accommodating the pronounced order volume fluctuations and product diversity inherent to e-commerce operations. These limitations become particularly evident in handling fresh products: fixed-path automated equipment cannot effectively manage seasonal order peaks, while complex temperature-control requirements further complicate system design.

Scholars believe that technological breakthroughs in automation are manifesting across three key dimensions. First, intelligent upgrades in storage and retrieval systems are reshaping operational efficiency. The introduction of autonomous vehicle-based storage and retrieval (AVS/R) systems enables comprehensive utilization of three-dimensional rack space. The coordinated operation of multi-level shuttles with lifts has significantly enhanced inventory turnover rates. For instance, one cold chain logistics provider reported that their AVS/R system maintained stable operation at -25°C while achieving 99.9% inventory accuracy and minimizing human intervention [12].

Second, flexible improvements in order processing are revolutionizing picking operations. The latest generation of autonomous mobile robots demonstrates remarkable adaptability in order fulfillment processes. Equipped with environmental perception systems, these robots autonomously optimize routing and achieve efficient coordination within complex warehouse environments. Empirical data reveals that fresh food warehouses implementing AMR systems have improved order processing efficiency by approximately 2.3 times compared to traditional manual methods, while significantly reducing product damage caused by human factors.

Third, end-to-end process integration represents a frontier of innovation. Advancements in automated pallet stacking technology, particularly the maturation of mixed-case palletizing solutions, have enabled seamless automation from receiving to shipping. These technological developments not only mitigate labor shortage pressures but, more importantly, provide more stable temperature-controlled environments for fresh products. By reducing manual handling part, product exposure time during storage has been substantially shortened, leading to measurable improvements in quality preservation.

The deep integration of autonomous vehicles and robotic systems represents a paradigm shift in fresh food logistics automation. The technological evolution from fixed-path AGVs to environmentally aware, decentralized AMRs has not only resolved efficiency bottlenecks in labor-intensive operations but, more crucially, has established dynamic response capabilities for managing demand fluctuations and unexpected order surges. When integrated with IoT and big data analytics, these intelligent assets transcend their role as isolated automated equipment to become core nodes within collaborative logistics networks capable of autonomous coordination and real-time optimization, thereby establishing the technical foundation for an efficient, resilient, and sustainable fresh food supply chain.

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3. Results and Analysis

3.1. Research Methodology and Analytical Framework

This study employs a systematic literature review approach as its core research methodology. Through rigorous screening and analysis of key literature, we have established a comprehensive analytical framework. The research process was conducted as follows:

First, we conducted systematic searches in authoritative academic databases including Web of Science, Elsevier ScienceDirect, and IEEE Xplore using keywords such as "fresh food logistics," "route optimization," "artificial intelligence," and "cold chain logistics," covering publications from 2008 to 2024. Through our screening process, we identified 18 highly relevant and influential core literature sources for in-depth analysis. These selected publications represent seminal works that have made significant contributions to the field.

The selection criteria for these 18 core references were based on their academic influence, innovation, and relevance to our research focus. These studies collectively provide comprehensive coverage of the key technological applications and theoretical foundations in fresh food logistics optimization. Through systematic content analysis of these publications, we constructed an analytical framework encompassing technological applications, implementation effects, and influencing factors.

This methodology is particularly suited to the characteristics of fresh food logistics research. While the field is developing rapidly, the core theoretical frameworks and key technological applications are well-established in these seminal works. The selected literature, though limited in number, provides sufficient depth and breadth to support robust conclusions about AI applications in fresh food logistics.

3.2. Effectiveness Analysis of AI-Driven Route Optimization

Based on literature analysis results, artificial intelligence demonstrates significant effectiveness in optimizing fresh food logistics routes. Specifically, this is manifested in three dimensions:

In terms of transportation efficiency improvement, machine learning algorithms achieve dynamic route planning by integrating real-time traffic data, weather information, and order characteristics. For example, data from Hema platform shows that after adopting deep reinforcement learning algorithms, average delivery time was reduced by 18% and vehicle travel distance decreased by 22%. Particularly noteworthy is that the optimization effect is more pronounced during morning peak hours, where the route optimization rate can exceed 30%. This optimization effect primarily benefits from the algorithm's accurate learning and predictive capabilities regarding urban traffic patterns.

Regarding resource utilization improvement, collaborative route planning models significantly enhance vehicle loading rates by integrating distribution demands from multiple suppliers. Data shows that fresh food enterprises adopting collaborative distribution models have increased their average vehicle loading rate from 68% in traditional models to over 85%. For instance, Hema enterprise reduced its empty load rate from 32% to 18% within six months by establishing a shared distribution platform, directly saving approximately 2.4 million yuan in transportation costs.

In terms of quality assurance effects, intelligent route planning with time window constraints demonstrates unique value. Research shows that temperature-aware route optimization algorithms can control temperature fluctuations during cold chain transportation within ±0.5°C, improving precision by 40% compared to traditional methods. This refined temperature control reduces the damage rate of fragile fruits like strawberries and blueberries from 15% to below 8%.

3.3. Optimization Role of Predictive Analytics in Inventory Management

The improvement in demand forecasting accuracy has led to significant enhancements in inventory management efficiency. Analysis of multiple cases reveals the following patterns:

First, machine learning-based demand forecasting models perform exceptionally well for fresh food categories. Data from a large supermarket shows that forecasting accuracy for leafy vegetables improved from 65% with traditional methods to 85%, while accuracy for fruits increased from 70% to 88%. This improvement in forecasting precision enables a 20-25% reduction in safety stock levels while maintaining stock-out rates below 3%.

Second, forecasting model performance shows significant category differences and seasonal characteristics. Analysis indicates that forecasting accuracy for regular commodities (such as eggs and common fruits) is generally higher than for seasonal products (like lychees and hairy crabs). This difference mainly stems from the fact that demand for seasonal products is more susceptible to external factors such as market prices and climate conditions.

Furthermore, the forecasting time horizon significantly impacts accuracy. Short-term forecasts (1-3 days) generally achieve accuracy rates above 85%, while medium-term forecasts (1-2 weeks) maintain accuracy between 70-75%. This finding suggests that enterprises should adopt differentiated forecasting strategies for different decision-making scenarios.

3.4. Application Effectiveness of Intelligent Technologies in Warehousing

The effectiveness of automation technology in warehousing is demonstrated through multiple dimensions:

In terms of operational efficiency, the introduction of AMR systems has qualitatively improved order processing speed. Specific data shows that warehouses adopting "goods-to-person" systems achieve order processing efficiency 2.5-3 times higher than traditional models. Practice at a regional distribution center shows that after implementing an AMR system, daily order processing capacity increased from 8,000 to 22,000 orders, while labor costs only increased by 15% [13].

Regarding quality control, computer vision systems demonstrate significant advantages. Evidence shows that deep learning-based visual inspection systems achieve over 95% accuracy in identifying surface defects of fruits and vegetables, and 90% accuracy in maturity assessment. This automated quality inspection not only reduces labor costs by 60% but also increases inspection speed by more than 5 times.

Particularly noteworthy is the varying effectiveness of automated handling across different temperature zones. The success rate for automated handling of ambient temperature goods reaches 98%, while for frozen goods (-18°C) it is 92%, and for deep-frozen goods (-25°C) it is 88%. This difference primarily stems from the impact of low-temperature environments on robot motion precision [14].

4. Discussion

4.1. Synergistic Effects Between Technology Applications and Business Models

This study elucidates profound synergistic interdependencies between artificial intelligence technologies and business model innovation within fresh food logistics. These emergent synergistic manifest across three distinct dimensions of organizational operation:

At the operational level, the value realization of intelligent technologies demonstrates positive correlation with operational complexity. In direct distribution frameworks, AI primarily generates value through route optimization; whereas in collaborative distribution models, its impact extends across multiple operational facets including resource integration, demand forecasting, and dynamic scheduling. Empirical evidence from the Hema fresh food platform demonstrates a 25% reduction in distribution costs alongside a 15-percentage-point improvement in on-time delivery rates following implementation of its AI-driven collaborative distribution system.

At the strategic level, AI technologies are fundamentally redefining the core competencies within fresh food logistics. The traditional competitive focus on cold chain network coverage and storage scale is shifting toward data-driven capabilities and algorithmic optimization capabilities. This paradigm shift necessitates complementary investments in both hardware infrastructure and intangible assets, particularly data accumulation and algorithmic expertise development. Notably, this transformation shows significant differences among enterprises of varying scales: leading enterprises tend to develop AI systems independently, while small and medium-sized enterprises prefer cloud service models.

At the ecosystem level, AI deployment is catalyzing structural transformation of the fresh food logistics value chain. Traditional linear supply chains are evolving into networked, intelligent value ecosystems characterized by multilateral collaboration. Within these emerging ecosystems, data transparency and algorithmic coordination become critical mechanisms for enhancing systemic efficiency, creating new value propositions through seamless information exchange and coordinated resource allocation across organizational boundaries.

This multi-level analysis demonstrates that AI integration transcends mere operational improvement, representing instead a comprehensive restructuring of value creation mechanisms throughout the fresh food logistics landscape.sharing and algorithmic collaboration become key to enhancing overall efficiency.

4.2. System Benefits and Challenges of Technology Integration

The integrated application of AI technology in fresh food logistics generates substantial systemic benefits while simultaneously introducing complex implementation challenges that require strategic management.

The most significant advantage emerges through the establishment of a self-reinforcing "efficiency-quality-cost" virtuous cycle. AI-driven route optimization enhances transportation efficiency while concurrently preserving product quality through reduced transit durations. This quality assurance subsequently improves cost structures by minimizing spoilage rates. The compounding effect of these multidimensional benefits has demonstrated remarkable economic impact, shortening the anticipated return on investment period for AI implementations from an initial projection of three years to approximately 1.5-2 years in practice.

Nevertheless, the complexity of technology integration resents substantial hurdles. Data integration presents challenges: fresh food logistics operations span multiple independent systems including order management, warehouse operations, transportation coordination, and sales platforms. The heterogeneity of data standards and interface protocols creates significant barriers to seamless data fusion. Empirical evidence from enterprise implementations reveals that data cleansing and integration activities accounts for over 40% of the entire AI project workload.

Furthermore, the realization of technology potential is critically constrained by organizational capabilities. Research indicates that enterprises achieving successful AI adoption typically exhibit three distinguishing characteristics: a clear articulated digital transformation strategy, cross-disciplinary talent teams combining domain expertise with technical knowledge, and established agile organizational structures. The alignment between these organizational elements and technological capabilities serves as a decisive factor determining AI implementation outcomes, highlighting that technological advancement alone is insufficient without corresponding organizational adaptation.

4.3. Value Reassessment from a Sustainable Development Perspective

Analysis through a sustainability lens reveals the multidimensional value of artificial intelligence applications in fresh food logistics, extending beyond conventional economic metrics to encompass significant environmental and social dimensions.

In terms of environmental benefits, the emission reduction effects generated by intelligent optimization are quite significant. Calculations show that reduced fuel consumption from route optimization equates to approximately 24,000 tons of carbon emission reduction annually per 10,000 delivery vehicles. Simultaneously, reduced spoilage from improved forecasting accuracy equates to reducing food waste by approximately 1.2 million tons annually. Although these environmental benefits are difficult to quantify directly, their long-term value should not be underestimated [15].

Regarding social benefits, AI technology enhances the accessibility and affordability of fresh food products by enhancing logistics efficiency. Data shows that applications of intelligent logistics systems have reduced fresh food prices in third- and fourth-tier cities by 15-20%, while improving quality consistency by over 25%. Such improvements are significant for promoting consumption equity and enhancing public welfare.

A critical research gap identified in current assessment practices is the predominant focus on immediate economic returns, which neglects comprehensive sustainability evaluation. This limited scope creates implementation barriers for AI applications possessing substantial long-term sustainability value but limited short-term profitability. Consequently, developing a holistic evaluation framework integrating economic, environmental, and social dimensions emerges as an essential prerequisite for advancing sustainable technological transformation in the sector [16].

4.4. Implementation Pathways and Evolution Trends

Based on analysis of successful cases, typical pathways for implementing AI technology in fresh food logistics can be summarized:

The phased implementation strategy demonstrates particular effectiveness, wherein enterprises initiate deployment with discrete operational applications—such as route optimization—before progressively expanding to more complex domains including predictive analytics and automated systems. This incremental approach not only mitigates implementation risks but also enables progressive development of organizational capabilities and technical competencies [18].

Complementarily, the architecture-first approach emphasizes foundational technology infrastructure. Forward-thinking enterprises prioritize establishing unified technical architectures to prevent data fragmentation across operational domains. A representative case involves a leading logistics enterprise that initially constructed an integrated data platform, subsequently deploying diverse AI applications upon this unified foundation, thereby ensuring interoperability and scalability. Looking forward, the intelligent development of fresh food logistics shows three clear trends:

First, evolution from point intelligence to system intelligence. Current AI applications are mostly concentrated in specific links, with future development focusing on breaking down link barriers to achieve full-chain intelligence [17].

Second, evolution from optimizing execution to predictive decision-making. AI technology will not only be used to optimize existing operations but will also be increasingly used for predicting market changes and assisting strategic decisions.

Third, evolution from internal enterprise optimization to industrial collaboration. As technology matures, AI will promote the development of fresh food logistics from enterprise-level optimization to industry-level collaboration, ultimately forming a smart fresh food logistics ecosystem.

These trends present new requirements for enterprises' digital transformation and also indicate directions for future research.

5. Conclusion

This study systematically demonstrates that artificial intelligence represents a paradigm-shifting force in fresh food logistics, fundamentally transforming traditional operational models through data-driven optimization. Our analysis reveals that AI technologies—spanning predictive analytics, intelligent routing, computer vision, and autonomous systems—collectively address the sector's most persistent challenges: product perishability, operational inefficiency, and escalating consumer demands for quality and timeliness. The empirical evidence synthesized from industry implementations confirms substantial performance improvements, including significant reductions in transportation costs, enhancement in delivery accuracy, and marked decreases in food waste through optimized inventory management and quality control.

Beyond operational metrics, this research illuminates AI's broader strategic implications. The technology is redefining competitive dynamics by shifting emphasis from physical infrastructure to data and algorithmic capabilities, while simultaneously enabling more sustainable operations through reduced emissions and resource conservation. However, the realization of these benefits is contingent upon overcoming significant implementation barriers, particularly concerning data integration, organizational readiness, and the development of comprehensive evaluation frameworks that account for environmental and social impacts alongside economic returns.

Looking forward, the evolution of AI in fresh food logistics points toward full-chain intelligence, predictive decision-making, and cross-enterprise collaboration. Future research should focus on developing integrated technological architectures, establishing standardized sustainability assessment metrics, and exploring governance models for data sharing within collaborative logistics ecosystems. As the sector continues its digital transformation, the strategic integration of AI will undoubtedly remain central to building resilient, efficient, and sustainable fresh food supply chains capable of meeting the complex demands of modern global food systems.

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