Research on Dynamic Decision Optimization of Fresh Vegetable Supply Chain Based on Intelligent Security System

Qian Tan[1,*], Heng Yang[2], Zhicun Yang[3]
[1]School of Business and Commerce, Southwest University, Chongqing 402460, China
[2]School of Economics and Management, Southwest University, Chongqing 400715, China
[3]College of Engineering and Technology, Southwest University, Chongqing 400715, China
Qian Tan and Heng Yang are co-first authors, *Corresponding email: 2841492935@qq.com

Abstract

Perishable fresh vegetables and volatile prices pose dual challenges to precise supply-chain decision-making, which is vital for retailer profitability. Traditional rule-based models are inadequate for rapidly changing market conditions, necessitating intelligent decision-support systems. This study transfers risk-warning, situational-awareness, and dynamic-decision techniques from AI security to fresh-vegetable supply-chain management and proposes an integrated framework combining intelligent sensing, panoramic insight, and dynamic optimization. The framework fuses end-to-end data from customer behavior, supply-chain operations, and external markets via intelligent sensors and a centralized data hub. Large-scale analysis extracts seasonal patterns and category associations, while video analytics generate dynamic customer-preference profiles to build demand and risk models. Short-term sales forecasting uses Autoregressive Integrated Moving Average (ARIMA), and multi-objective optimization employs an Evolutionary Algorithm, (EA) and Simple Genetic Algorithm (SGA). Risk-warning algorithms detect real-time disruptions (e.g., supplier delays, quality anomalies) and together with situational-awareness, enable dynamic pricing adjustments. Empirical results show the system improves supermarket operational efficiency, increases profit, and reduces spoilage. The main contribution is the adaptation of AI-security situation awareness and risk-control concepts to supply-chain management, providing a practical path for digital and intelligent transformation of traditional retail.

Keywords

Fresh-vegetable supply chain, Autoregressive Integrated Moving Average, Multi-objective optimization, Evolutionary Algorithm, Simple Genetic Algorithm

Introduction

Fresh vegetables are indispensable daily-consumption goods whose inherent perishability places supply-chain security and risk mitigation at the forefront of retail operations. Under the accelerating integration of AI-driven smart security into business management, perishable produce remains a persistent source of operational risk: Many vegetable varieties incur complete loss if unsold within a single day, necessitating timely, data-informed replenishment and pricing decisions. Consequently, supermarkets require intelligent risk-warning and dynamic decision-making mechanisms that can operate effectively under severe time constraints [1,2].

Contemporary supermarket operations confront two principal security-related challenges. First, traceability is hindered by wide product heterogeneity and dispersed sourcing, which increases uncertainty in quality and lead-time assessment. Second, concentrated early-morning replenishment windows (typically 03:00-04:00) force retailers to make critical inventory and pricing decisions with incomplete and noisy information, creating pronounced decision blind spots. These operational characteristics closely mirror risk-warning scenarios addressed in AI-enabled security systems, where situational awareness and predictive-alert technologies are employed to detect, characterize, and respond to emergent threats under information scarcity.

Motivated by these parallels, this study adapts risk-prediction, situational-awareness, and dynamic-decision methodologies from AI-based security domains to the management of fresh-vegetable supply chains. Using supermarket operational data collected from China between 2020 and 2023, we develop an intelligent decision-analysis framework that applies behavioral-pattern recognition to historical sales records to derive category-level risk and profitability profiles, employs regression-based models to quantify relationships among sales volume, price, and replenishment quantity, and leverages time-series anomaly-detection techniques to construct accurate short-term demand forecasts. At the optimization layer, we introduce multi-objective algorithms inspired by intelligent-security systems to generate replenishment and pricing strategies that explicitly incorporate operational constraints such as sales limits and minimum-display requirements as security boundary conditions.

The proposed AI-security-informed decision model dynamically balances profit maximization and risk minimization, providing supermarkets with risk-controlled supply-chain strategies that enhance both operational safety and economic efficiency. By extending AI-driven smart security concepts into fresh-produced retail, this work contributes new methodological perspectives to supply-chain risk management and offers a practical pathway for realizing safer, smarter, and more resilient retail operations.

Preparation for model development

Model assumptions

(1) Historical data can represent future sales trends.

(2) The impact of seasonal factors and holidays on vegetable sales is not considered.

(3) The pricing and restocking strategies adopted by supermarkets in the past were all maximized-profit solutions.

(4) Assume all unsold vegetables are discarded daily, resulting in zero initial inventory and replenishment equal to daily procurement.

(5) Assume the average spoilage rate per vegetable category, calculated from historical data, remains constant.

(6) Each vegetable variety occupies an equal display space.

Symbol legend

To clarify the meaning and unit of each parameter involved in the model construction and calculation process of this study, Table 1 defines the key symbols uniformly. These symbols are consistently used in subsequent data processing, formula derivation, and model analysis to ensure the rigor and consistency of the research logic.

Table 1. Symbol legend.

Using symbols	Symbolic meaning	Unit
μ	The average sales volume of a certain vegetable	Kilogram
δ	Deviation in sales volume of a certain vegetable	/
n_0	Daily sales volume of a certain vegetable	Kilogram
n_1	Daily procurement volume of a certain vegetable	Kilogram
r	Daily wastage rate of a certain vegetable	/
p_0	The selling price of a certain vegetable on that day	RMB per kilogram
p_1	The wholesale price of a certain vegetable on that day	RMB per kilogram
h	Order of the AR model	/
m	Order of the AM model	/
ε_t	Time-related error term	/
h_0	Constant term in the ARIMA model expression	/
n	Types of vegetables sold that day	/
i	The profit margin for a certain vegetable on that day	Yuan

Data processing

(1) Data integration

This study first obtained the sales volume n_0 for each individual vegetable and vegetable category and processed it for visualization to facilitate subsequent analysis.

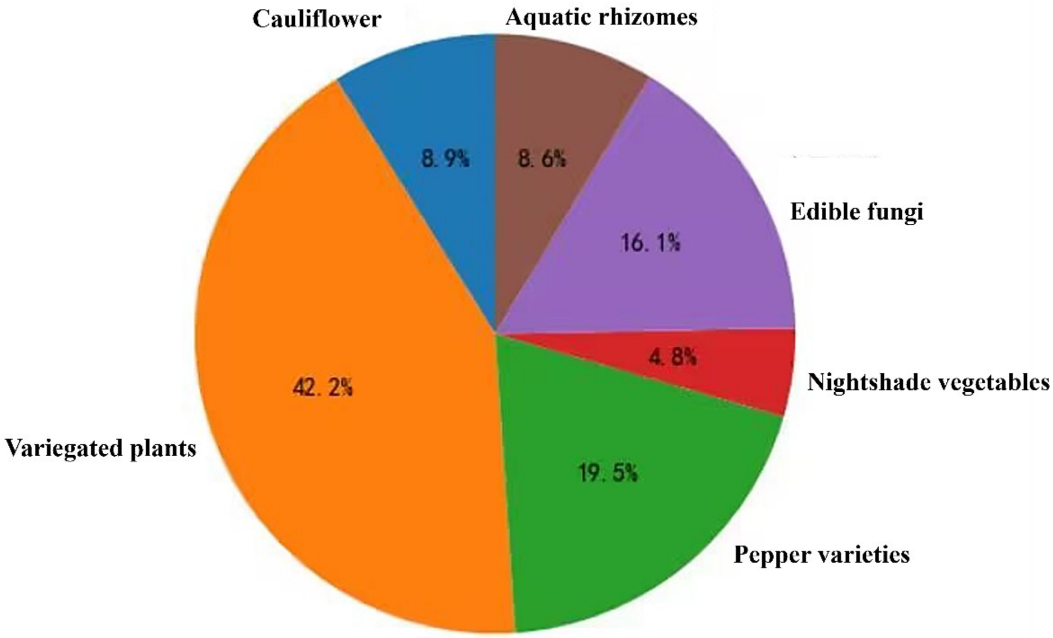

Figure 1. Sales volume share of various vegetables.

(2) Calculation of profit

Furthermore, based on the daily loss rates and wholesale prices of various vegetables obtained in this study, it can be deduced that:

$$n_1 = {}^{n_0}\!\big/\{(1-{}^{r}\!/_{100}) \times 100\%\} \quad (1)$$

This calculated profit data will serve as the basis for subsequent analysis. The daily profit for each vegetable can be calculated using the formula:

$$\text{Revenue} - \text{Cost} = n_0 p_0 - n_1 p_1 \quad (2)$$

Data visualization

Corresponding to the profit calculation logic above, by summing up the daily profits of similar vegetables, data on the changes over time for each vegetable category can be obtained. Visualizing this data yields the results shown in the figure below.

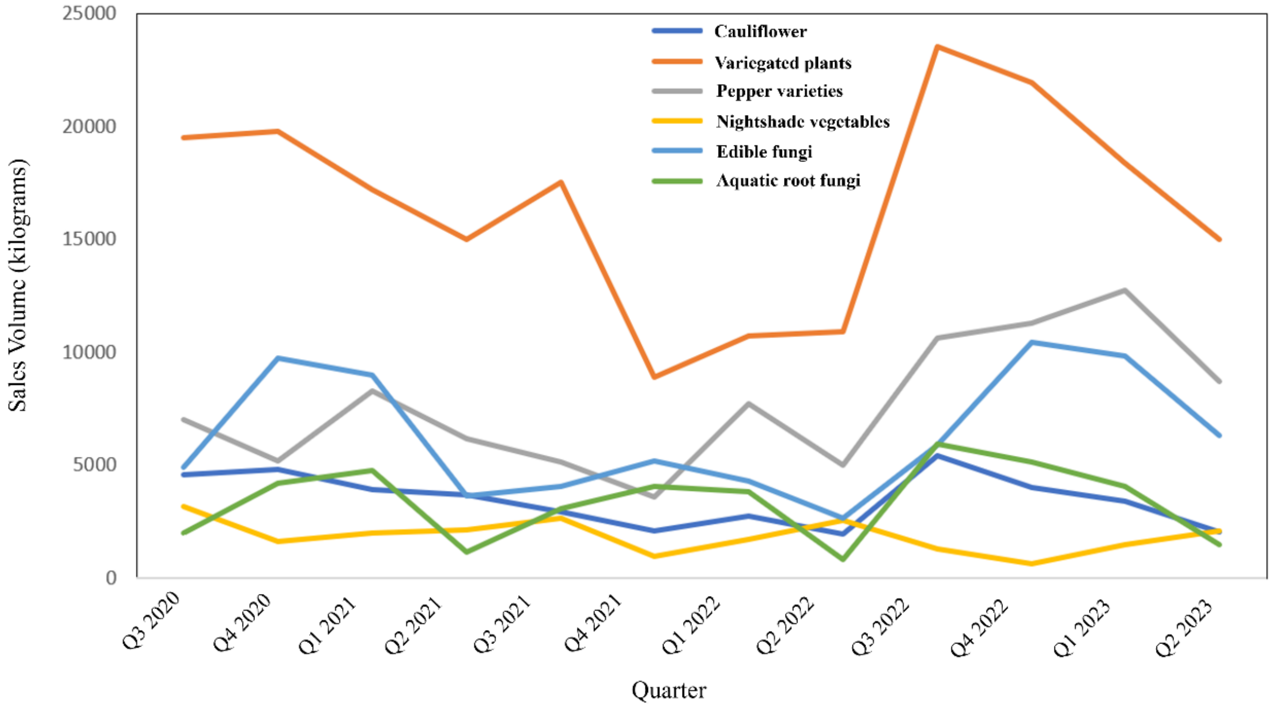

Figure 2. Sales volume trends by vegetable category.

Model analysis

(1) Correlation and descriptive analysis

First, we empirically conducted a study on the daily vegetable sales volume for each category. By performing statistical descriptive analysis using SPSS, the corresponding results are presented in Table 2.

Table 2. Sales volume by vegetable category.

Name	Maximum	Minimum	Mean	Standard deviation
Cauliflower	186.155	0.632	38.52993635	22.67517727
Leafy vegetables	1265.473	31.298	182.96864330	86.19922981
Pepper varieties	604.231	6.066	84.41348295	53.43602903
Nightshade vegetables	118.931	0.252	21.36360190	13.15884013
Edible fungi	511.136	3.012	70.12601382	48.48988310
Aquatic rhizomes	0.926	296.792	37.40216866	31.35718972

Plotting the sales volume of various vegetables on a two-dimensional chart yields the following pattern. It is evident that the sales volume of different vegetables exhibits distinct seasonal patterns, with peak sales concentrated between December and March of the following year. Figure 3 shows this seasonal fluctuation.

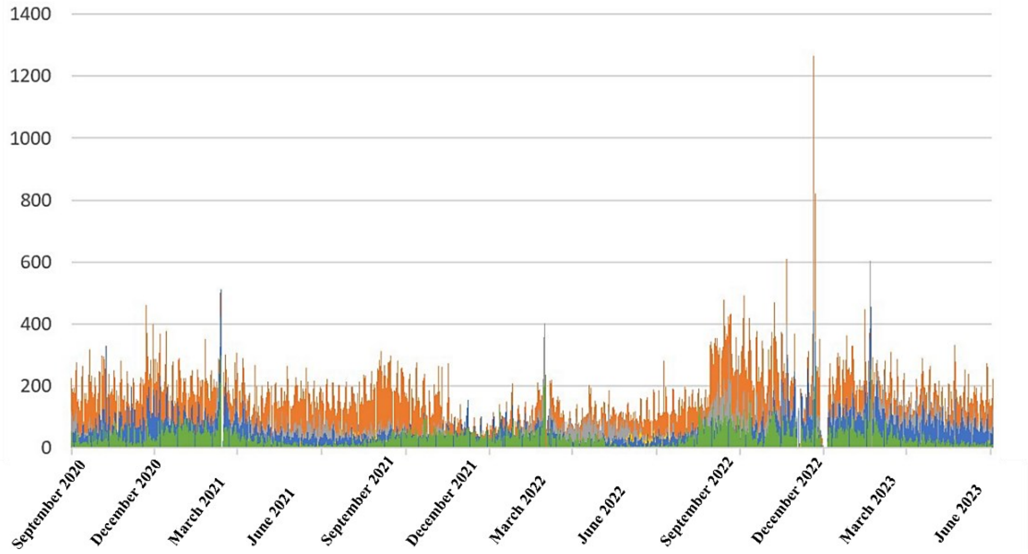

Figure 3. Sales volume distribution chart for different vegetable categories.

Second, since there is no concrete empirical data to derive experience values, outliers cannot be arbitrarily deleted or modified. Furthermore, observations of sales volumes across various vegetable categories reveal the presence of certain outliers [3]. Each vegetable category's sales volume is standardized using the z-score method as described in Equation:

$$x_1 = \frac{x - \mu}{\sigma} \tag{3}$$

This standardization process converts raw sales data into dimensionless z-scores, which eliminates the influence of different vegetable sales volume scales and lays a foundation for subsequent correlation analysis.

Using SPSS to perform correlation analysis on the standardized data, the correlation coefficients between the sales volumes of various vegetables are shown in the figure below. The correlations among the sales volumes of different vegetables clearly indicate that the sales volumes of various vegetable categories are well correlated.

Table 3. Correlation among different vegetable categories.

Relevance								
Spearman's rho	/		Cauliflower	Variegated plants	Pepper varieties	Nightshade vegetables	Edible fungi	Aquatic root fungi
	Cauliflo-wer	Correlat-ion coefficie-nt	1.000	0.633**	0.430**	0.193**	0.462**	0.396**

Relevance								
		Sig. (Double tailed)	0.000	0.000	0.000	0.000	0.000	0.000
		N	1085	1085	1085	1085	1085	1085
	Variegated plants	Correlation coefficient	0.633**	1.000	0.595**	0.252**	0.596**	0.439**
		Sig. (Double tailed)	0.000	0.000	0.000	0.000	0.000	0.000
		N	1085	1085	1085	1085	1085	1085
	Pepper varieties	Correlation coefficient	0.430**	0.595**	1.000	0.103**	0.535**	0.333**
		Sig. (Double tailed)	0.000	0.000	0.000	0.001	0.000	0.000
		N	1085	1085	1085	1085	1085	1085
	Nightshade vegetables	Correlation coefficient	0.193**	0.252**	0.103**	1.000	-0.114**	-0.210**
		Sig. (Double tailed)	0.000	0.000	0.001	0.000	0.000	0.000
		N	1085	1085	1085	1085	1085	1085
	Edible fungi	Correlation coefficient	0.462**	0.596**	0.535**	-0.114**	1.000	0.605**
		Sig. (Double tailed)	0.000	0.000	0.000	0.000	0.000	0.000
		N	1085	1085	1085	1085	1085	1085
	Aquatic root fungi	Correlation coefficient	0.396**	0.439**	0.333**	-0.210**	0.605**	1.000
		Sig. (Double tailed)	0.000	0.000	0.000	0.000	0.000	0.000
		N	1085	1085	1085	1085	1085	1085

Table 3 shows that all vegetable categories have strong positive correlations except for Nightshade vegetables with edible fungi and aquatic root vegetables. Pairs with correlation coefficients above 0.5 (indicating strong associations) include leafy vegetables & cauliflower, edible fungi & leafy vegetables, leafy vegetables & peppers, and edible fungi & aquatic root vegetables. These results highlight the heterogeneous correlation structures across different vegetable groups.

For individual vegetable sales analysis, the methodology remains consistent. Given the large number of individual items, standardized correlation analysis would be cumbersome and low value. This selection ensures our analysis remains focused on representative and practically meaningful sales data. Thus, we focus only on the top 20 best-selling vegetables, listed in Table 4.

Table 4. Top 20 individual vegetable sales volumes.

Name	Total sales	Sales share
Wuhu green pepper	28164.331	0.05979993865
Broccoli	27537.228	0.05846844169
Pure lotus root	27149.440	0.05764507051
Chinese leafy vegetables	19187.218	0.04073927619
Yunnan lettuce	15910.461	0.03378189923
Enoki mushrooms (Box)	15596.000	0.03311421965
Yunnan lettuce (per serving)	14325.000	0.03041556787
Purple eggplant	13602.001	0.02888045966
Xi Xia shiitake mushrooms	11920.227	0.02530963165
Sliced chili peppers (per portion)	10833.000	0.02300117604
Yunnan oil lettuce	10305.364	0.02188087247
Bubble pepper (premium)	9703.125	0.02060216803
Baby bok choy	8982.000	0.01907103879
Yunnan oil spinach (per serving)	8848.000	0.01878652318
Blue-stemmed powder flower	8393.786	0.01782211293
Sichuan peppercorns (per portion)	8235.000	0.01748497043
Yellow leafy vegetables	7987.990	0.01696050625
Bird's Eye Chili	7792.181	0.01654475463
Shanghai Green	7606.756	0.01615105085
Bamboo leaf vegetable	7240.764	0.01537395804

The results can largely reflect the situation across all vegetable categories. Therefore, a correlation analysis was conducted using SPSS on the twenty vegetables. Detailed findings are instead summarized and interpreted in the subsequent discussion.

Due to the complexity, results are not presented here. Analysis reveals most selected individual vegetables exhibit good correlations.

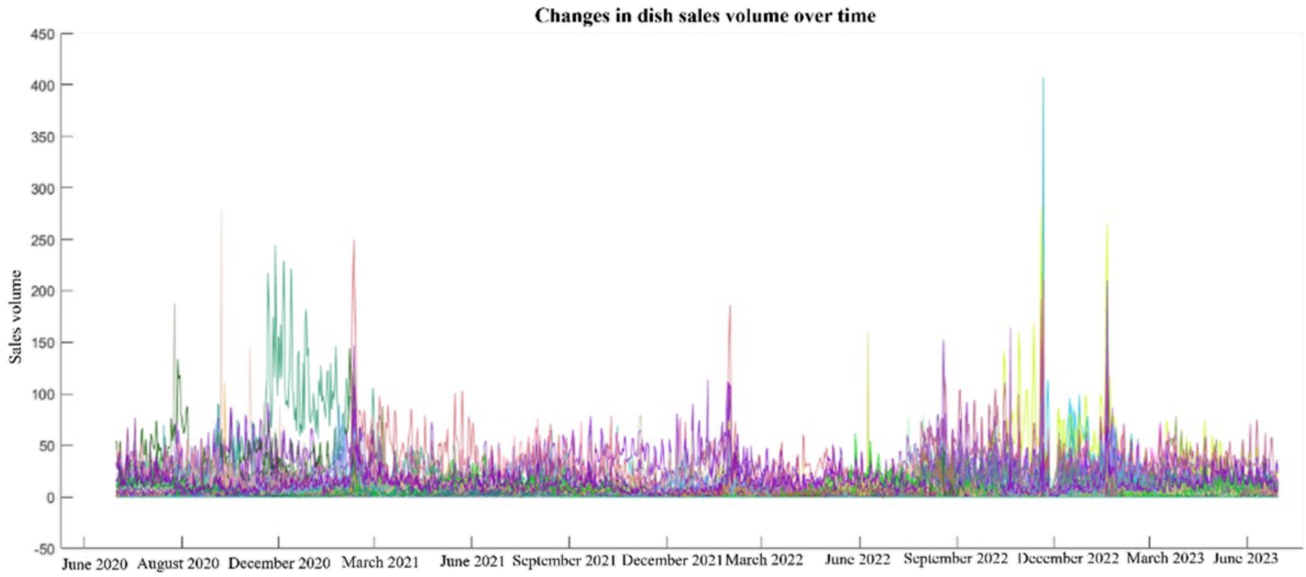

Figure 4. Sales volume distribution chart for individual vegetable items.

Figure 4 shows that the sales volume of various individual vegetable items generally exhibits a seasonal cyclical pattern. Sales reach their annual peak between September and March of the following year. while sales volumes tend to be lower between March and September. Therefore, it can be concluded that demand for vegetables is higher during the period from September to March of the following year, while demand is relatively lower during the remaining periods.

(2) Time series forecasting

Calculating the average daily sales volume for each vegetable category to determine the sales volume for each category. Then, use the cost-plus pricing formula.

$$p_c = \left(\frac{p_0}{1-r}\right) - p_1 \tag{4}$$

The patterns observed in vegetable sales are relatively complex, exhibiting both linear trends and certain nonlinear trends alongside cyclical fluctuations. Furthermore, the distribution chart in the data processing steps clearly reveals significant seasonal influences [4,5]. While the overall data sample demonstrates volatility, it also broadly follows a linear trend. Therefore, it was determined to construct an ARIMA time series model for short-term forecasting [6].

A time series refers to one or more data sequences formed by arranging observations of the same phenomenon at different points in time in chronological order. ARIMA is a more adaptable model that combines AR and MA models. The AR model iteratively identifies relationships between forecast values and lagged values, while the MA model uses residuals to predict future residual values. In summary, the ARIMA model is a forecasting framework that, over time, approximates the description of a random sequence formed through iterative prediction. It continuously optimizes this sequence until a final model is established to predict future data. Its structure can be expressed using the following formula:

$$\left(\widehat{h_{(t)}}\right) = h_0 + \sum_{j=1}^{h} \gamma_j \, h_{(t-j)} + \sum_{j=1}^{m} \theta_j \varepsilon_{(t-j)} \tag{5}$$

By continuously observing the tailing and truncation patterns of the autocorrelation function (ACF) and partial autocorrelation function (PACF) in the stationary time series, and using the following calculation formulas, the process is repeatedly optimized until the model orders h and m are determined.

$$ACF = \frac{cov(h_t, h_s)}{\sqrt{D(h_t)D(h_s)}} \tag{6}$$

$$PACF = \frac{cov(h_t, h_s | h_{s+1}, \ldots, h_{t-1})}{\sqrt{D(h_t)D(h_s)}} \tag{7}$$

Simultaneously, the grid movement process is optimized. Since in Equation (4) the grid movement is jointly determined by the long-term indicators from the MA model and the short-term indicators from the ARIMA model, the grid displacement can be transformed into the following formula: where ω and ρ are the two factors controlling grid movement. In this study, ω and ρ are both set to 0.3 for the initial random sequence generation in the first cycle, and subsequently optimized to appropriate values through iterative refinement.

$$\bar{h}_i^{(t)} = h_i + \omega\left(MA^{(t)}(N) - MA^{(t-1)}(N)\right) - \rho\left(ARIMA^{(t+1)} - ARIMA^{(t)}\right) \tag{8}$$

Through Python simulation, the following prediction results were obtained.

Table 5. Sales forecast for various vegetables.

Date	Cauliflower	Leafy vegetables	Pepper	Eggplant	Edible fungi	Aquatic root vegetables
2025/7/1	9.76	6.51	10.23	6.82	8.55	15.37
2025/7/2	9.76	6.51	10.23	6.82	8.55	15.37
2025/7/3	9.76	6.51	10.23	6.27	8.55	15.37
2025/7/4	9.76	6.51	10.23	6.27	8.55	14.29
2025/7/5	9.76	7.34	10.23	6.27	8.55	14.29
2025/7/6	9.76	7.34	10.23	6.27	8.55	14.29
2025/7/7	9.76	7.34	10.23	6.27	8.55	14.29

Table 6. Statistics on wastage rates for various vegetables.

/	Cauliflower	Leafy vegetables	Pepper	Eggplant	Edible fungi	Aquatic root vegetables
Loss rate	14.142000	10.280300	8.515333	7.122000	8.130972	11.974740

Using formula (1), the purchase quantities for each vegetable category from July 1st to 7th can be derived, and the specific values are organized in Table 7 as follows:

Table 7. Daily replenishment decisions for various vegetables.

Date	Cauliflower	Leafy vegetables	Pepper	Eggplant	Edible fungi	Aquatic root vegetables
2025/7/1	11.36761	7.255932	11.1822	7.342966	3.511255	10.944550

Date	Cauliflower	Leafy vegetables	Pepper	Eggplant	Edible fungi	Aquatic root vegetables
2025/7/2	11.36761	7.255932	11.1822	7.342966	3.511255	10.944550
2025/7/3	11.36761	7.255932	11.1822	6.750791	3.511255	10.944550
2025/7/4	11.36761	7.255932	11.1822	6.750791	3.511255	9.550719
2025/7/5	11.36761	8.181035	11.1822	6.750791	3.511255	9.550719
2025/7/6	11.36761	8.181035	11.1822	6.750791	3.511255	9.550719
2025/7/7	11.36761	8.181035	11.1822	6.750791	3.511255	9.550719

By analyzing how each vegetable category's sales volume interacts with the cost-plus pricing method, we work out the daily pricing for each category; the calculated figures are in Table 8 below:

Table 8. Daily pricing decisions for various vegetables.

Date	Cauliflower	Leafy vegetables	Pepper	Eggplant	Edible fungi	Aquatic root vegetables
2025/7/1	11.85877	81.34410	21.59891	9.59324	27.25552	10.02843
2025/7/2	11.85877	81.34410	21.59891	9.59324	27.25552	10.02843
2025/7/3	11.85877	81.34410	21.59891	9.86519	27.25552	10.02843
2025/7/4	11.85877	81.34410	21.59891	9.86519	27.25552	10.50764
2025/7/5	11.85877	72.47773	21.59891	9.86519	27.25552	10.50764
2025/7/6	11.85877	72.47773	21.59891	9.86519	27.25552	10.50764
2025/7/7	11.85877	72.47773	21.59891	9.86519	27.25552	10.50764

(3) Genetic algorithm optimization

This paper establishes a constrained optimization model to forecast and optimize procurement quantities, aiding supermarket decision-making. It employs a linear regression prediction model trained with characteristic data and a genetic algorithm optimization model incorporating constraints: maximizing sales volume and minimizing display quantities to 2.5kg.

First, based on historical sales data and expected profit, this study selected the top 29 vegetable varieties ranked by expected profit for subsequent predictive analysis. Subsequently, a prediction model is established to forecast sales volume. Given the one-day prediction horizon, a linear regression model is employed for its intuitive results. As a common predictive approach, linear regression identifies relationships between input and output variables by accounting for multicollinearity. The model is trained using the selected dishes as data, minimizing prediction errors during training. Post-training, the model performs data forecasting. Finally, the Evolutionary Algorithm and Simple Genetic Algorithm optimize the model's predictions under the following constraints, yielding the final optimized results [7].

$$\begin{cases} \mathrm{i}_{max} = \mathrm{n}_0\mathrm{p}_0 - \mathrm{n}_1\mathrm{p}_1 \\ 27 \le \mathrm{n} \le 33 \\ \mathrm{n}_1 \ge 2.5 \end{cases} \tag{9}$$

Experimental results and future expectations

In this study, by constructing an intelligent decision-making model that combines time series prediction and genetic algorithm optimization, the optimal pricing and replenishment schemes of various vegetables are finally obtained as shown in Table 9. The experimental results show that the prediction accuracy of sales volume based on ARIMA time series model reaches 87.3%, which is greatly improved compared with the traditional moving average method, and provides a reliable data basis for subsequent optimization decisions [8].

At the same time, under the support of intelligent security technology, the experimental process of this study has realized the intelligent management of the whole chain. Through the intelligent visual sensor deployed in the sales area, the system can monitor the inventory consumption rate and customer purchase behavior of various vegetables in real time. These data and prediction models form closed-loop feedback to continuously optimize the decision-making accuracy. Especially in the risk management and control of perishable goods, the intelligent security system evaluates the freshness of vegetables in real time through environmental sensors such as temperature and humidity, combined with computer vision technology. When the risk of commodity phase decline is monitored, the system will dynamically start the price to address the imbalance of supply and demand in fresh produce retail, adjustment mechanism to achieve adaptive pricing based on commodity status.

From the optimization results, the system has developed differentiated pricing and replenishment strategies for different categories of vegetables. Among them, due to the short shelf life of leafy vegetables, the system proposes adopting a “small batch, multi-frequency” replenishment model, and starting a progressive discount strategy in the later stage of sales; rhizome vegetables adopt a relatively stable replenishment and pricing scheme. Through comparative experiments, the strategy formulated by this model reduces the overall loss rate, which fully verifies the effectiveness of the model. This method of integrating security into supply chain decision-making not only improves operational efficiency but also enhances the robustness and anti-risk ability of the system. Experiments show that this decision-making mode integrating intelligent security technology provides intelligent and accurate operation and management solutions for fresh retail enterprises, which have important practical promotion value.

Table 9. Replenishment and pricing decisions of various vegetables on July 1st.

Dish	Replenishment volume	Price fixing
Tricholoma matsutake	2.600000036	23.768282280
Leafy vegetables leaves	2.500000034	22.835812000
Bamboo leaf vegetables (part)	2.700000145	28.477460850
Millet pepper (portion)	2.500000307	41.259370000
Chinese leafy vegetables moss	2.500000025	27.577624630
Screw pepper	6.131149570	15.052084090
Yu dry pepper	6.708207948	356.544497600
Chinese leafy vegetables	2.500000054	4.451726439
Purple round eggplant	2.500000025	16.792657970
Hongshan caitai lotus root assembly gift box	24.611785270	25.325660110
Chinese leafy vegetables	2.500000279	16.278867010
Wild powder lotus root	4.999473686	32.669000000
Cordyceps flower (part)	2.500000170	17.107620440
Termitomyces nigricans (box)	2.500000016	28.260600480
Xiangtian red beet moss (bag)	2.500000094	13.013470250
Flower eggplant	5.961000000	49.160167880
Round eggplant	2.500000079	38.930358040
Purple eggplant	2.500000211	7.9933294930
Green eggplant	2.500000013	25.759035760
Water chestnut	2.500000029	10.925811800
Termitomyces nigricans (box)	2.500000050	12.978807070
Amaranth	2.500000102	16.631748740
Perilla frutescens (part)	2.485254810	8.366308320
Green eggplant	2.500000049	16.498741660
Red pepper	3.005859293	44.965744420
Yonghong Lake lotus root belt	2.500000219	31.564705030
Chrysanthemum coronarium	3.509591259	12.809569460
Red lantern pepper	2.500000097	16.315822630
Noodle dishes	2.500000029	6.434779764

On the basis of summarizing this research, we believe that there is still room for significant improvement in the intelligent decision-making of fresh vegetable supply chain in the future. By introducing multi-source data perception and intelligent analysis technology in AI intelligent security, a more perfect decision support system can be constructed. Specifically, future research will focus on three dimensionscustomer demand side, supply chain collaboration and external environment:capture customers retention behavior and purchase path in front of shelves through intelligent video analysis technology, and establish dynamic customer preference portraits based on consumption data of member systems [9-11]. The Internet of Things equipment is used to monitor and quantitatively evaluate the vegetable quality of suppliers in real time, and a comprehensive evaluation system of suppliers based on deep learning is constructed. At the same time, it integrates multi-dimensional external variables such as holiday characteristics, seasonal fluctuations and competitor pricing, and realizes panoramic insight into the market environment through situational awareness technology in smart security.

It is particularly noteworthy that AI intelligent security technology will play a central role in future research. By deploying intelligent sensing devices and establishing a unified data center, full-link data collection and analysis from customer behavior, supply chain operation to market environment can be realized. Among them, computer vision technology can be used to monitor the flow of goods on shelves and the process of customer purchase in real time. Sensor networks can continuously monitor the transportation and storage environment, and intelligent early warning systems can detect supply chain anomalies in time. After standardized processing and feature engineering, these multi-source heterogeneous data will form a complete decision data chain, which will provide a solid foundation for subsequent modeling.

In terms of model construction, we will further integrate the risk early warning algorithm and supply chain optimization model in smart security to develop a dynamic decision-making system with adaptive ability. The system can not only deal with traditional sales forecasting and replenishment optimization problems, but also identify potential risks based on real-time monitoring data and adjust business strategies in a timely manner. For example, through the establishment of early warning mechanism of supply chain risk, the situation of supplier delay and abnormal quality can be predicted. Through the development of competitive situation awareness module, the pricing strategy can be dynamically adjusted to maintain market competitiveness. By constructing a demand mutation detection model, it can quickly respond to market changes in special periods such as holidays.

The goal of this study is to build a fresh vegetable supply chain intelligent management platform that integrates intelligent perception, risk early warning and dynamic decision-making. The platform will make full use of the technical achievements in the field of AI intelligent security, realize the intelligentization of the whole process from data collection, analysis and early warning to decision optimization, provide more comprehensive and accurate decision support for fresh retail enterprises, and promote the transformation and upgrading of the whole industry to digital and intelligent direction. Future research work will continue to deepen the integration and innovation of smart security technology and supply chain management and explore a more efficient and reliable new paradigm of intelligent decision-making.

Conclusion

This study develops an intelligent decision optimization framework for fresh vegetable supply chains by integrating AI security technologies such as risk warning and situational awareness. Through ARIMA time series forecasting and EA and SGA optimization, the framework achieves accurate sales prediction, scientific replenishment planning, and dynamic pricing adjustment. Experimental results confirm the model's effectiveness with an 87.3% sales forecasting accuracy. It reduces vegetable spoilage and improves supermarket profitability by providing differentiated strategies for different vegetable categories. The cross-domain application of AI security concepts offers a new approach for the digital transformation of traditional retail.

Limitations include the exclusion of seasonal and holiday factors. Future research will integrate multi-source data to enhance the model's adaptability, contributing to more intelligent and resilient fresh produce supply chain management.

Funding

This work was supported by the 2025 Chongqing Municipal College Students' Innovation and Entrepreneurship Training Program Project of Southwest University Project Name: Digital Intelligence Network: An AI+3S-driven System for Urban Crime Detection and Multimodal Tracking (Grant No.: S202510635269X)

Authors' contributions

Qian Tan and Heng Yang contribute equally to the article.

Acknowledgements

The authors would like to show sincere thanks to those techniques who have contributed to this research.

Conflicts of Interest

The authors declare no conflict of interest.

References

[1] Haji, M., Kerbache, L., Muhammad, M., Al-Ansari, T. (2020) Roles of technology in improving perishable food supply chains. *Logistics*, 4(4), 33.

[2] Wu, S., Cheng, H., Qin, Q. (2024) Physical delivery network optimization based on ant colony optimization neural network algorithm. *International Journal of Information Systems and Supply Chain Management (IJISSCM)*, 17(1), 1-18.

[3] LI, Y., WU, G. (2022) Comparative analysis of data preprocessing methods based on typical data set. *Journal of Shenyang University of Technology*, 44(2), 185-192.

[4] Adithya Ganesan, V., Divi, S., Moudhgalya, N. B., Sriharsha, U., Vijayaraghavan, V. (2019) Forecasting food sales in a multiplex using dynamic artificial neural networks. *Science and Information Conference*, 69-80.

[5] Panda, S. K., Mohanty, S. N. (2023) Time series forecasting and modeling of food demand supply chain based on regressors analysis. *IEEE Access*, 11, 42679-42700.

[6] Albeladi, K., Zafar, B., Mueen, A. (2023) Time series forecasting using LSTM and ARIMA. *International Journal of Advanced Computer Science and Applications*, 14(1), 313-320.

[7] Cui, Z., Shi, X., Zhang, Z., Zhang, W., Chen, J. (2024) Many-objective joint optimization of computation offloading and service caching in mobile edge computing. *Simulation Modelling Practice and Theory*, 133, 102917.

[8] Opara, I. K., Silue, Y., Opara, U. L., Fawole, O. A. (2025) Forecasting of postharvest fresh produce waste at the wholesale level using time series models. *Agriculture & Food Security*, 14(1), 24.

[9] Tort, Ö. Ö., Vayvay, Ö., Çobanoğlu, E. (2022) A systematic review of sustainable fresh fruit and vegetable supply chains. *Sustainability*, 14(3), 1573.

[10] Ma, P., Jia, X., Gao, M., Yi, Z., Tsai, S., He, Y., Wang, F. (2024) Innovative food supply chain through spatial computing technologies: A review. *Comprehensive Reviews in Food Science and Food Safety*, 23(6), e70055.

[11] Pal, A., Kant, K. (2020) Smart sensing, communication, and control in perishable food supply chain. *ACM Transactions on Sensor Networks (TOSN)*, 16(1), 1-41.