

Supply Chain Collaboration Mechanisms Driven by Demand Orchestration in Omni-Channel Retail Environments

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Abstract: Driven by mobile Internet and big data technology, the omni channel retail model has developed rapidly. Its core feature is that product portfolio decisions directly affect profitability. Faced with challenges such as diversified customer demands, high uncertainty in the supply chain system (including daily operational risks and extreme event risks), inconsistent customer behavior time (such as perceived product value changing with the lifecycle), and risk avoidance characteristics of decision-makers, the traditional assumption of "rational economic man" is no longer applicable. This study focuses on the decision-making problem of omni channel supply chain operations. By constructing distributed robust optimization models, stochastic programming models, and dual objective robust optimization models, combined with duality theory, linearization techniques, Monte Carlo simulations, and other methods to deal with uncertainty, we specifically use mean CVaR to measure risk, WMCVaR to characterize cost fluctuations, quasi hyperbolic discount functions, and latent category Logit models to characterize demand time inconsistency and customer heterogeneity selection processes. The results show that the distributed robust optimization model performs better in risk avoidance and profit risk trade-off; The hybrid order fulfillment strategy (such as combining SFS and BOPS) is superior to a single strategy, as it can provide diversified products and is not affected by changes in unit fulfillment costs; The parameters such as demand ratio, inventory capacity, and fulfillment cost significantly affect the decision results (such as saving more costs when the online demand ratio is high). The model demonstrates effectiveness and robustness in small and medium-sized cases, and can cope with daily operational risks and extreme event risks. By integrating behavioral operation management and uncertainty planning theory, a decision-making framework for omni channel supply chain considering decision-makers' risk avoidance and customer time preferences was constructed. Technical methods for handling uncertainty were proposed, providing practical guidance for omni channel retail enterprises to formulate optimal operational strategies. In the future, behavioral factors such as disappointment avoidance and bounded rationality can be further expanded, uncertainties in transportation costs and delivery times can be included, multi-party competition coordination mechanisms can be studied, and the application value of the model can be verified by combining actual enterprise data.

1 Introduction

Against the backdrop of the rapid development of omni channel retail[1], the integration of online and offline has become a new trend in the retail industry. Traditional brick and mortar

retail is facing a wave of store closures due to online retail impact, while online retail is also experiencing a slowdown in traffic dividends and price wars, forcing companies to turn to omnichannel. The uncertainty of the operation environment of the omni channel supply chain has increased, including "daily operation risks" such as daily cost, price and demand fluctuations, as well as "failure risks" caused by extreme events such as natural disasters and economic crises (such as semiconductor shortages caused by epidemic, and food price fluctuations caused by the conflict between Russia-Ukraine conflict). Behavioral operation management highlights value: The traditional assumption of "rational economic agents" ignores the limited rationality of decision-makers, but in reality, decision-makers often exhibit risk aversion (pursuing profit stability) and customer time preferences (cross period value perception differences affecting purchasing decisions). The existing research has three limitations: it is mostly based on random programming models with known distributions, which do not fully coordinate the two types of uncertainties; Insufficient research on the integration of omnichannel feature decision-making (product mix, distribution layout, order fulfillment) and behavioral factors (risk avoidance, time preference); Lack of effective methods to characterize omnichannel behavioral characteristics. This study focuses on the supply chain collaboration mechanism driven by demand coordination in omnichannel retail, aiming to incorporate decision-makers' risk avoidance and customer time preference behavior, bridge the gap between theory and reality, and enhance the practical guidance of management insights. The objectives of the paper are divided into three levels: theory, model and method, and application. The theoretical level aims to broaden the depth and breadth of research on omnichannel supply chain operation decision-making considering behavioral factors in uncertain environments, and establish a research framework; Construct multiple optimization models at the level of models and methods (such as two-stage distributed robust optimization models based on mean CVaR, WMCVaR, WCVaR, WMQD[2], dual objective robust optimization models, etc.), and propose techniques such as Monte Carlo simulation[3], linear transformation, duality theory, CVaR approximation to solve the models; At the application level, the effectiveness of the model is verified through numerical examples, providing decision-making references for omnichannel retail enterprises to cope with uncertain risks and formulate optimal operational strategies. The contribution is reflected in three aspects: theoretical expansion promotes the integration of omnichannel supply chain management and behavioral operation management, providing theoretical support; Method innovation proposes uncertain optimization model processing techniques, providing methodological references for similar research; The practical guidance model can solve practical decision-making problems such as product portfolio, inventory, pricing, and distribution layout, helping decision-makers cope with uncertainty and ensuring the stable and long-term development of the supply chain.

2 Correlation theory

2.1 A review of research on omnichannel retail supply chain operation decision-making

The research on the decision-making problem of omnichannel retail supply chain operation considering behavioral factors in uncertain environments has broad practical background and important theoretical significance. Academic trend analysis shows that the publication volume and citation frequency of literature related to omnichannel retail have steadily increased from 2011 to 2023; The overall number of papers and citations in the fields of supply chain risk management and

behavioral operation management showed an upward trend from 1996 to 2023, indicating that related topics continue to receive academic attention. Omnichannel retail refers to enterprises meeting consumers' purchasing needs at any time, place, and method through multiple channels such as offline, online, and mobile e-commerce, providing a seamless shopping experience. Its development brings challenges of synergy, integration, networking, intelligence, and digitization, and the academic community conducts research on issues such as pricing, inventory management, returns, and channel selection. The research on omnichannel operation decision-making focuses on multiple modes, such as offline experience online purchase (Showrooming), online purchase offline pickup (BOPS), online purchase offline return (BORS), online reservation offline pickup (ROPS), etc. Showrooming behavior research shows that physical showrooms can reduce inventory, while virtual showrooms may lower profits, availability information, or render physical showrooms ineffective; Empirical evidence shows that BOPS strategy increases offline sales and customer traffic, but its profit impact depends on operating costs, pricing strategies, and market characteristics; BORS and inventory management research focuses on the impact of return rates and channel convenience on pricing and revenue. In a competitive environment, power structure and first mover advantage affect the effectiveness of BOPS strategy implementation. Existing research has explored the implementation conditions and performance impact mechanisms of omnichannel strategies in monopolistic and competitive scenarios, providing theoretical basis for retailer operational decision-making. However, further research is needed to combine behavioral factors with uncertain environments.

2.2 A review of research on supply chain behavior operation management in uncertain environments

In the practice of supply chain management, decision-makers need to pay attention to the uncertainty factors both inside and outside the system. Ignoring uncertainty may lead to decision-making errors, low efficiency, and even economic losses. To this end, scholars have delved into uncertain supply chain management problems through methods such as stochastic programming, robust optimization, and distributed robust optimization. Random programming is suitable for scenarios with parameter uncertainty and known probability distribution, and can be divided into two-stage and multi-stage models. The two-stage model is widely used in strategic planning of bioenergy supply chains, optimization of secondary distribution of refined oil, etc. It balances costs and service levels through Lagrange relaxation decomposition[4] or accelerated L-shaped methods; The multi-stage model deals with long-term decisions such as optimizing the transportation of biofuel supply chains, and achieves efficient solutions through nested decomposition[5] or sampling average approximation algorithms, with better numerical performance than the two-stage model. Robust optimization assumes that the probability distribution of parameters is unknown and is divided into two categories: those based on uncertain sets (box, ellipse, or polyhedron sets) and those based on scenarios. The former, such as linear programming robust equivalent form, suppresses the negative impact of demand uncertainty, while the latter combines solution robustness and model robustness to handle production fluctuations or demand uncertainty. Hybrid robust stochastic optimization further integrates the two types of parameters and is applied to closed-loop supply chains, omni channel supply chains for fresh products, and other scenarios. Distributed robust optimization combines statistics and optimization theory, constructs uncertain sets through moment information/statistical distance, and applies them to fields such as rescue logistics and supply chain interruption risk. Decision optimization is achieved through semi definite programming or mixed integer linear programming combined with opportunity constraints. Behavioral operation management studies the impact of bounded rationality, risk aversion,

inconsistent time preferences, and other behaviors on the system, such as using CVaR, mean variance balance risk and cost, and hyperbolic discount function to analyze intertemporal decisions. Although existing research clarifies uncertainty handling methods and analyzes the theoretical background of behavior, there is insufficient research on the joint optimization of omnichannel product portfolio inventory pricing, and the interaction effects of multiple factors of uncertainty and decision maker consumer behavior need to be deepened. In the future, it is necessary to build an optimization method system driven by omnichannel behavior, embed order fulfillment strategies, systematically analyze the impact of the behavioral characteristics of both parties on decision-making, and fill the gap in the joint research of multiple behavioral preferences and multiple uncertain factors.

3 Research method

3.1 A review of research on operational decision-making of omnichannel retail supply chain under uncertain environment

This section delves into the relevant concepts and theoretical foundations of omni channel retail supply chain operation decision-making in uncertain environments, covering the definition and characteristics of omni channel retail supply chain, uncertainty planning theory, and behavioral operation management theory. Omnichannel retail supply chain refers to the retail form in which enterprises interact with customers through various channels such as brick and mortar stores, websites, call centers, direct mail and catalogs, service terminals, door-to-door services, social media, and mobile devices, aiming to meet customers' purchasing needs at any time, any place, and any way, and provide an undifferentiated shopping experience. Its core supply chain consists of interconnected and influential network systems such as suppliers, manufacturers, logistics service providers, warehouses, and retailers, including supply nodes, facility nodes, distribution nodes, and market nodes. Its characteristics are mainly reflected in two aspects: cross channel and node information co construction and sharing. Cross channel is reflected in the logistics system's organic integration of basic functions such as transportation, warehousing, processing, packaging, distribution, loading and unloading, and information processing. Combining and efficiently integrating, Realize resource interoperability and network optimization; Node information co construction and sharing are achieved through mobile internet and big data technology, supporting inventory information sharing strategies to improve operational efficiency, avoid inventory shortages or backlogs, and establish close connections between cross channel nodes to achieve information exchange. The theory of uncertain programming covers methods such as stochastic programming, robust optimization, and distributed robust optimization. Stochastic programming is suitable for scenarios with parameter uncertainty and known probability distribution, and is divided into expected value models and chance constrained programming models. The expected value model [6] takes the form of

$$\min E[f(x, \xi)], s, t. E[g_j(\chi, \xi)] \leq 0, j = 1, 2, \dots, m, x \in X$$

The form of opportunity constrained planning is

$$Pr\{g_j(\chi, \xi) < 0, J = 1, 2, \dots, M\} > a$$

Or mixed form

$$Pr\{g_j(\chi, \xi) < 0\} > a_j, Pr\{g_k(\chi, \xi) < 0\} > a_k,$$

Robust optimization assumes that the probability distribution of parameters is unknown and aims to find solutions that satisfy constraints in any situation and achieve optimal goals in the worst-case scenario. It is divided into two categories: scenario based and uncertain set based. Scenario based robust optimization commonly uses absolute robustness, robust bias, and relative robustness criteria.

Absolute robustness is achieved through

$$\min_{x \in X} \max_{\xi \in \Xi} f(x, \xi)$$

Implementation, robust bias through

$$\min_{x \in X} \max_{\xi \in \Xi} [f(x, \xi) - f^*(x, \xi)] f(x, \xi)$$

Implementation, relative robustness achieved through

$$\min_{x \in X} \max_{\xi \in \Xi} \frac{f(x, \xi) - f^*(x, \xi)}{f(x, \xi)}$$

realization; Robust optimization based on uncertain sets is solved by converting uncertain parameters into deterministic forms, such as linear programming models

$$\max C^T x, s. t. a_i^T x \leq b_i, i = 1, 2, \dots, m,$$

among which $a_{ij} = \bar{a}_{ij} + \widehat{a}_{ij} \xi_j, \xi \in U$, Convert the model into

$$\max C^T x, s. t. a_i^T x + \|\widehat{a}_i^T X\|_* \leq b_i$$

Behavioral operation management studies the impact of human behavior and cognitive processes on system operation, with a focus on behavioral factors such as bounded rationality, risk aversion, and time preference. Risk aversion research uses tools such as expected value, mean variance, Value at Risk (VaR), Conditional Value at Risk (CVaR), and Quantile Deviation (QD). Among them, the CVaR method is the most popular because it satisfies monotonicity and subadditivity, and balances operating costs and risks through the mean CVaR criterion. It is applied in scenarios such as newsboy model inventory decision-making and supply chain optimization with uncertain supply and demand; Time preference research focuses on time inconsistency behavior in intertemporal decision-making, using hyperbolic discount functions or quasi hyperbolic discount functions to characterize changes in consumer demand. It is applied to scenarios such as dynamic pricing, changes in product lifecycle demand, and periodic review inventory systems to capture decision-makers' higher attention to short-term returns and preference reversal phenomena. This chapter lays the theoretical foundation and provides theoretical and methodological support for subsequent research by summarizing relevant concepts, methods, and theories.

3.2 Omnichannel retail product portfolio and inventory joint optimization framework

This framework focuses on the joint decision-making problem of distribution network layout, inventory optimization, and order fulfillment strategies in the omni channel retail supply chain under uncertain environments. The research focuses on a multi-level, multi product, and multi cycle logistics network, covering the supply chain network composed of suppliers, distribution centers, brick and mortar stores, and customers. The goal is to achieve operational optimization by integrating online and offline channels. The delivery network adopts a hybrid order fulfillment strategy (such as SFD-SFS), where SFS utilizes the existing brick and mortar store network to fulfill online orders, requiring an upgrade to the brick and mortar stores backend inventory management system and a fixed cost investment; SFD responds to demand through economies of scale in distribution centers, but involves long-distance transportation costs. Decision making needs to consider inventory capacity constraints between distribution centers and brick and mortar stores, supplier supply uncertainty, and horizontal transfer elasticity strategies (inventory allocation between distribution centers to address supply-demand imbalances). The model construction adopts a two-stage distributed robust optimization method, using WMCVaR as the risk measurement criterion, and combining box and polyhedral uncertain sets to characterize the imprecision of parameter probability distribution, to derive a robust equation that is easy to handle. The objective function balances cost and risk through the mean CVaR criterion, combines Monte Carlo sample approximation method to process CVaR calculation, and is transformed into a linear programming equivalent form based on strong duality theory, supporting direct solution through optimization

software. The study emphasizes that the layout of the distribution network needs to balance costs and risks, and the mixed strategy demonstrates advantages in balancing profit and risk. Brick and mortar stores inventory allocation prioritizes meeting offline demand, and online orders are fulfilled through distribution centers or brick and mortar stores. Unmet demand is not transferred across channels, providing theoretical support and operational guidance for the practice of omnichannel retail supply chain.

3.3 Equivalent Model of Omnichannel Distribution Inventory Joint Optimization

In the joint optimization of omnichannel supply chain distribution network layout and inventory under uncertain environment, the objective function value increases linearly with the increase of risk avoidance parameters and adjustment parameters, and the trend is consistent at the confidence levels of 0.9 and 0.7; Polyhedral uncertain sets have larger scales and more conservative decisions, and their objective function values are higher than box shaped ones. Therefore, it is necessary to choose appropriate uncertain sets to hedge the risk of inaccurate probability distributions. Comparing distributed robust optimization (DRO) and nominal stochastic programming (SP) models, at a confidence level of 0.9, the objective function values of both increase with the increase of risk avoidance parameters, while SP has a lower optimal value due to accurate distribution information; DRO uses box/polyhedron sets to hedge distribution risks, with box sets performing better (maximum distributed robust pricing not exceeding 0.15%/0.60%). Out of sample analysis shows that under 100 random scenarios, the worst-case cost of DRO is 38851.54-39901.54 lower than SP, with a smaller interquartile range (48083.07/47753.83 vs SP 79293.77) and better robustness. Sensitivity analysis shows that the proportion of online demand (5% -85%) significantly affects costs; The expected cost difference between the mixed order fulfillment (IF) strategy and the single strategy increases sharply with the increase of the proportion at low online ratios, and decreases at high online ratios. However, the total fulfillment cost of IF is lower and there are fewer stockouts. At high online ratios, the advantage weakens but still outperforms the single strategy. The model integrates online and offline demand and mixed fulfillment strategies, combined with inventory constraints, supply uncertainty, etc. It distinguishes strategic and tactical decisions through two-stage stochastic programming, measures risk using expected cost and CVaR, characterizes parameter inaccuracy using DRO method, and transforms it into a solvable linear programming through strong duality theory, which is solved by CPLEX, providing theoretical and methodological support for optimizing the omni channel supply chain.

4 Results and discussion

4.1 Analysis of Factors Influencing Omnichannel Supply Chain Decision making

Time preference behavior [7] affects decision results through both short-term and long-term factors. Under different combinations of values, the Pareto front shows that as the long-term factor increases, both the conditional risk value and the expected total utility show an upward trend. Similarly, as the short-term factor increases, both show an upward trend, indicating that customers are more sensitive or practical in their perception of product fashion value. Retailers tend to adjust order quantities to avoid unsold risks or stock shortages. The analysis of variable ordering costs shows that fluctuations in unit ordering costs alter the optimal product mix and expected profit. For example, in the fixed unit cost scenario, the first cycle ordering quantity decreases and profit decreases by 1.24%. In the highly variable cost scenario, it prompts an increase in orders in the second cycle and a decrease in orders in the third cycle, affecting product mix and demand satisfaction. The analysis of brick and mortar stores capacity shows that the increase in inventory

capacity drives the expected profit increase, while the fulfillment volume of brick and mortar stores increases and the fulfillment volume of distribution centers decreases. At the same time, the replenishment cost increases and the inventory holding cost of distribution centers decreases. Retailers reduce fulfillment costs by increasing replenishment costs to increase profits, but excessive inventory capacity does not expand the product portfolio size, as some product operating costs cannot be offset by sales revenue. Comparing the cost analysis of unit fulfillment with mixed fulfillment strategy and single strategy, it is found that the expected profit under mixed strategy is always higher than that under single strategy. Although the total fulfillment cost is higher, adjusting the order fulfillment volume of brick and mortar stores and distribution centers can balance the replenishment cost and inventory holding cost, achieving profit optimization. Sensitivity analysis further verifies the impact of key parameters: confidence level and probability distribution of uncertain parameters affect expected profit and conditional risk value. When the degree of risk avoidance increases, replenishment strategies become more conservative, and expected profit and conditional risk value decrease; The mixed fulfillment strategy is still superior to a single strategy when the unit fulfillment cost increases, as the fulfillment cost of brick and mortar stores is lower than that of distribution centers. Retailers prioritize the use of brick and mortar stores inventory, but due to inventory capacity limitations, unfulfilled orders are completed by distribution centers; When the market demand distribution is different, the expected order quantity decreases as the probability of optimistic scenarios decreases. The risk avoidance model is more conservative in non-extreme optimistic scenarios, effectively balancing optimality and robustness, and meeting the risk avoidance needs of decision-makers

4.2 Model experiment

Omnichannel order fulfillment is complex, and SFS (online purchase offline pickup) and BOPS (online purchase in store self-pickup) are the core strategies of retailers. SFS utilizes store inventory to shorten delivery time and meet time sensitive needs, which is adopted by approximately one-third of retailers; BOPS supports product inspection, reduces return costs, enhances user experience, attracts customer flow, stimulates consumption, and strengthens competitiveness. The order fulfillment strategy directly affects inventory allocation and product flow, and choosing the appropriate strategy is crucial for retailers. The supply chain structure [8] is a three-tier network consisting of multiple suppliers, retailers (including distribution centers and brick and mortar stores), and customers. Retailers need to determine the SFS strategy and BOPS service provision for brick and mortar stores before the sales season (i.e. selecting shipping or self-pickup points); At the beginning of each week during the sales season, orders are placed with suppliers, who then transport the products to the distribution center. The distribution center decides on the replenishment quantity for each brick and mortar stores; Every weekend, it is necessary to decide whether to meet the demand for home delivery through brick and mortar stores or distribution centers, as well as offline and BOPS needs. The model construction is based on customer time preference behavior and price dependence characteristics to establish a demand function. A quasi-hyperbolic discount function [9] is used to characterize time preferences, and a total demand expression is formed by combining the price elasticity demand function. Omnichannel order fulfillment involves complex decisions, with SFS (store fulfillment of online orders) and BOPS (online purchase in store self-pickup) as the core strategies. SFS shortens delivery time to meet sensitive needs, adopted by approximately one-third of retailers; BOPS supports product inspection, reduces return costs, enhances user experience, and stimulates consumption. The total profit includes revenue, cost, and penalty items, while constraints include ordering, inventory balance, and service level (such as demand fulfillment probability $\geq 1 - \alpha$). The distributed robust optimization

model is based on WMQD/WMCVaR, defining VaR and CVaR, with the objective function being semi-infinite programming. Combining duality theory and approximate transformation of CVaR, the uncertain set is defined through the A norm, balancing risk and profit, adapting to partially known scenarios of probability distribution, and improving decision robustness. Finally, an equivalent model form that is easy to solve is obtained through auxiliary variable transformation. Joint chance constraint [10] transforms a constraint set containing auxiliary variables by introducing dual variables. When the probability distribution of uncertain parameters belongs to a specific set, the minimum term in the objective function can be transformed into an equivalent form through dual theory deduction, and the equivalent transformation under different constraint conditions can be proved separately. For example, joint chance constraint is transformed into a linear constraint set containing auxiliary variables and dual variables; When the probability distribution of uncertain parameters belongs to a specific set, the distributed robust optimization model of omni channel supply chain can be transformed into a linear programming form through minimum operator, duality theory, and CVaR approximation method. This equivalent model clarifies the objective function, constraint conditions, and decision variable range, ensuring the robustness and solvability of the model in uncertain environments, and providing an easy-to-handle theoretical framework support for the layout of omni channel distribution networks and inventory control.

4.3 Effect analysis

Under the rise of omnichannel retail, supply chain decision-making needs to focus on product portfolio, inventory, pricing, distribution layout, and joint optimization of order fulfillment. Comparison of order fulfillment strategies shows that the expected profits of SFS, BOPS, and mixed strategy (IFF) decrease with increasing unit fulfillment costs, but IFF has a significant profit advantage when SFS costs exceed the threshold and always outperforms the single BOPS strategy. In terms of network layout, the increase in SFS costs will lead to a decrease in the number of SFS brick and mortar stores in IFF, and BOPS brick and mortar stores will dynamically adjust. The analysis of demand ratio shows that within the range of online demand [0.1, 0.8], the profits of all three strategies decrease, but IFF has a more prominent advantage in high online demand. The study verifies the robustness of mixed strategies under cost fluctuations and demand changes through distributed robust optimization and stochastic programming models, combined with numerical examples, providing empirical support for the optimization of omni channel supply chains. In the demand ratio analysis section, when the online demand ratio changes within the range of [0.1, 0.8], the expected profits under all three order fulfillment modes show a decreasing trend. Table 1 shows that as online demand increases, the advantages of adopting both SFS and BOPS strategies gradually emerge;

Table 1 Numerical Comparison of Different Strategies in Omni-Channel Supply Chain

Parameter Identifier	SFS Strategy Value	BOPS Strategy Value	IFF Strategy Value
0.1	1,662,000	1,658,500	1,655,900
0.2	1,651,500	1,648,500	1,646,400
0.3	1,642,200	1,639,600	1,637,900
0.4	1,635,100	1,627,300	1,630,500
0.5	1,625,700	1,617,800	1,623,000
0.6	1,612,800	1,608,300	1,615,400
0.7	1,600,100	1,598,800	1,607,900
0.8	1,588,000	1,589,300	1,601,050

Further comparison of the profit differences of the three modes under different demand ratios indicates that as online demand increases, the profit difference between using both strategies gradually increases, and the strategy needs to be adjusted according to changes in demand. Table 2 shows the changes in distribution network layout under different demand ratios, indicating that as online demand increases, the number of brick and mortar stores implementing SFS and BOPS strategies also increases. However, there will not be a situation where all brick and mortar stores implement a certain strategy, as their inventory capacity is limited and BOPS demand needs to be prioritized.

Table 2 Comparison of Optimal Network Deployment under Different Online Demand Proportions

Online Demand Proportion	IFF Strategy Deployment	SFS Strategy Deployment	BOPS Strategy Deployment	SFS & BOPS Strategy Deployment
0.1	[0, 0, 0]	[1, 0, 0]	[0, 0, 0]	[1, 0, 1]
0.2	[0, 0, 1]	[0, 1, 1]	[0, 0, 0]	[0, 1, 1]
0.3	[0, 1, 1]	[0, 1, 1]	[0, 1, 0]	[1, 0, 1]
0.4	[1, 0, 1]	[0, 1, 1]	[0, 1, 0]	[1, 0, 1]
0.5	[1, 1, 1]	[0, 1, 1]	[0, 1, 0]	[1, 0, 1]
0.6	[1, 1, 1]	[0, 1, 1]	[0, 1, 1]	[1, 1, 0]
0.7	[1, 1, 1]	[0, 1, 1]	[0, 1, 1]	[1, 1, 0]
0.8	[1, 1, 1]	[0, 1, 1]	[0, 1, 1]	[1, 0, 1]

In the uncertain environment of omni channel supply chain decision-making, within the range of service level violation probability [0.1, 0.5], an increase in violation probability will increase expected profits but reduce ordering/replenishment costs, requiring a balance between profitability and long-term development. The extension of the product's popularity period (3 → 7) significantly increases the objective function value, expected profit, and brick and mortar stores order fulfillment, while BOPS demand remains stable due to high priority and high penalty costs. An increase in short-term factors (fashion sensitivity) requires a quick response to a decrease in demand, while an increase in long-term factors (practicality) tends to increase ordering to prevent stockouts. An increase in price sensitivity will reduce profits and order quantities, and the dependence of demand on price needs to be considered. Decision making needs to comprehensively consider multidimensional parameters such as product life cycle, time preference (short/long term factors), price elasticity, order fulfillment methods, demand ratios, and service levels. Through model optimization and sensitivity analysis, supply chain synergy efficiency and profitability can be improved, providing theoretical support and practical guidance for omni channel retail.

5 Conclusion

The core of mobile Internet and big data driving the development of omni channel retail is that product portfolio decisions directly affect profitability. The research focuses on joint decision-making of omni channel supply chain under uncertain environment, covering product portfolio, inventory, pricing, distribution layout and order fulfillment. It is transformed into mixed integer linear programming through distributed robust optimization, stochastic programming model and dual theory, linearization method, and verified with numerical examples. The key conclusions include: distributed robust optimization models are better in risk avoidance and profit risk trade-off; The hybrid order fulfillment strategy (such as combining SFS and BOPS) is superior to a single strategy and is not affected by changes in unit fulfillment costs; Parameters such as demand ratio and inventory capacity significantly affect decision-making. The research contribution lies in integrating behavioral operation management and uncertainty planning theory, enriching the

decision-making theory of omnichannel supply chain, and enhancing the flexibility of the model. Limitations include not considering other behavioral preferences, return decisions, etc. In the future, behavior factors can be expanded, transportation cost uncertainty can be included, and the model can be validated with actual enterprise data.

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