

Research on Data-Driven Optimization of Return Merchandise Resale Strategies

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ABSTRACT

Against the backdrop of rapid development in the digital economy, China's e-commerce industry has experienced explosive growth, accompanied by the persistent industry pain point of high return rates. Return rates in fast-moving consumer goods sectors such as apparel and cosmetics are generally high, with some live-streaming e-commerce platforms experiencing return rates exceeding 60%, directly causing industry average annual loss costs to exceed standards and severely constraining the sustainable development of the e-commerce industry. Some e-commerce platforms, in an effort to reduce merchants' return costs, have introduced algorithmic strategies such as "high-refund population shielding," yet these have sparked large-scale algorithmic discrimination controversies due to single metrics and insufficient transparency, both damaging consumers' legitimate rights and undermining market transaction fairness. This paper takes "bidirectional fairness" as its core orientation, focusing on the three-party interest balance of "user-merchant-platform," and constructs a data-driven return merchandise resale optimization system integrating multi-dimensional indicators of "merchandise damage degree-user preference-merchant responsibility ratio." The research employs literature research, empirical analysis, questionnaire surveys, and case analysis methods, based on return records and user behavior data from a major domestic e-commerce platform's apparel category from 2022-2024, to verify the practical effects of the optimization strategies. Results demonstrate that the proposed optimization strategies can effectively reduce algorithmic discrimination complaints in the apparel industry, decrease industry loss costs, and significantly improve the secondary transaction rate of returned merchandise. This research fills the research gap in algorithmic discrimination avoidance in the return merchandise resale field, enriches data-driven reverse logistics management theory, and provides important theoretical support and practical reference for e-commerce platform return management practices, relevant legal and regulatory improvements, and healthy industry development.

KEYWORDS

Data-driven; Return merchandise resale; Bidirectional fairness; Three-party interest balance; Algorithmic discrimination; Information disclosure

1. INTRODUCTION

1.1. Research Background

1.1.1. Industry Status

With the popularization of digital technology and the transformation of consumption patterns, online shopping has become the primary mode of daily consumption for residents. According to National Bureau of Statistics data, China's national online retail sales reached 15.5225 trillion yuan in 2024, surpassing the 15 trillion yuan threshold. However, alongside the industry's rapid development, high return rates have emerged as a prominent derivative problem, particularly notable in categories such

as apparel and cosmetics. Industry reports indicate that return rates in certain categories generally maintain a high range of 30%-50%, with categories such as women's clothing potentially experiencing even higher rates. This high-frequency return behavior not only brings enormous logistics, warehousing, and operational pressure to merchants but also causes serious resource waste—research indicates that a large number of returned goods cannot be resold due to improper handling and are ultimately destroyed or landfilled, which completely contradicts the concepts of green consumption and circular economy. To address these challenges, retailers are actively adopting measures such as charging return fees, shortening return windows, providing more precise sizing tools, and upgrading return processing technology to control costs and improve efficiency.

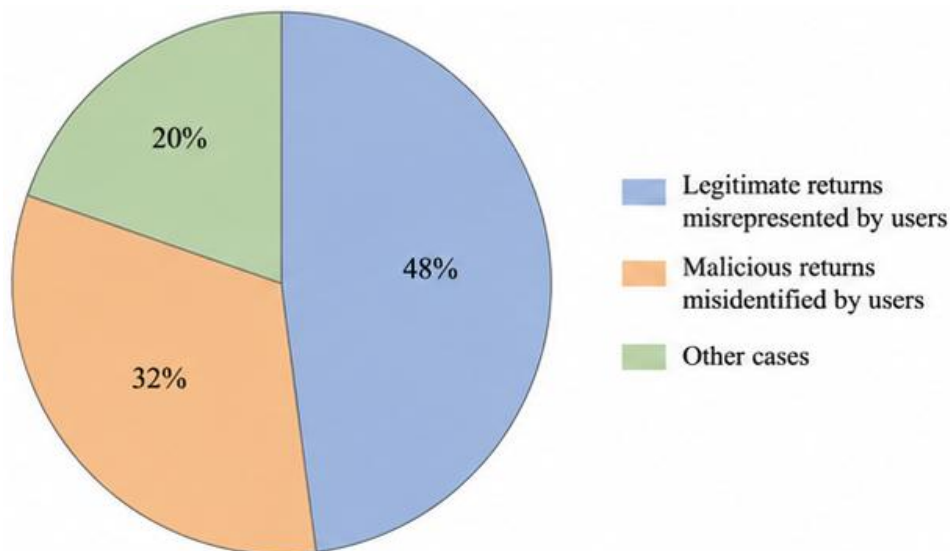


Figure 1. Trends in Apparel Industry Return Rates and Loss Costs

1.1.2. Traditional Dilemma

The return merchandise resale strategies currently adopted by e-commerce platforms and merchants mostly aim to control merchant costs, exhibiting numerous drawbacks. On one hand, the targeted distribution mechanism for returned goods is opaque—some platforms prioritize pushing returned goods with higher defect levels to low-spending or new users, ignoring user consumption preferences and right to know. On the other hand, algorithmic strategies such as "high-refund population shielding" and "return rate threshold limits" use only historical refund data as a single metric, lacking precise attribution of return reasons, resulting in normal return consumers being misjudged and blocked at significant rates. Taking the "high-refund population shielding" incident on Taobao as an example, a large number of users who normally returned goods due to product quality issues were labeled as "high-risk users" and unable to enjoy normal return rights, triggering over 100,000 user complaints and severely affecting platform credibility.

1.1.3. Driving Factors

At the policy level, China's "Interim Measures for Seven-Day No-Reason Return of Online Purchased Goods" explicitly requires merchants to fulfill information disclosure obligations for secondary sales of returned goods, marking key information such as "secondary circulation" and "minor defects." However, market supervision department spot check data shows that in 2024, merchants failing to fulfill return goods labeling obligations still accounted for 28%, with some merchants even disguising seriously defective products as new goods for sale, infringing on consumers' right to know. At the market level, with the enhancement of consumer rights protection awareness, demand for fairness in return goods transactions has become increasingly strong—most consumers indicate willingness to purchase clearly labeled secondary circulation goods, but have zero acceptance of return goods resale behavior with opaque information. The strengthening of policy supervision and the transformation of

market demands are forcing the industry to build fair, efficient, and transparent return goods re-circulation mechanisms.

1.2. Research Significance

1.2.1. Theoretical Significance

Existing return merchandise resale research mostly focuses on single dimensions such as reverse logistics path optimization and cost control, neglecting the balanced coordination of "user-merchant-platform" three-party interests, and research on algorithmic discrimination in the return field is relatively scarce. This paper breaks through the traditional "merchant cost priority" research perspective, constructs a three-party interest balance analysis framework under the guidance of "bidirectional fairness," incorporates algorithmic discrimination avoidance and information disclosure mechanisms into the return merchandise resale strategy system, enriches the application scenarios of data-driven reverse logistics management theory, algorithmic ethics theory, and three-party game theory, fills the research gap in algorithmic discrimination avoidance in the return merchandise resale field, and provides new theoretical perspectives and analytical frameworks for subsequent related research.

1.2.2. Practical Significance

The multi-dimensional data-driven return merchandise redistribution model, information disclosure mechanism, and bidirectional supervision tools proposed in this paper can directly respond to industry pain points such as "high-refund population shielding" and "opaque return goods information," achieving "user-merchant-platform" three-party win-win. For e-commerce platforms, optimization strategies can enhance platform credibility and user stickiness; for merchants, they can precisely match return merchandise with target users, reducing secondary losses and customer complaint rates; for consumers, they can guarantee transaction fairness and right to know, improving the consumption experience. At the same time, they can provide important practical reference for market supervision departments to improve return merchandise information disclosure systems and regulate e-commerce algorithmic discrimination behavior.

1.3. Research Content and Core Issues

1.3.1. Core Research Content

The core research content of this paper revolves around three major modules: first, constructing a multi-dimensional data-driven return merchandise redistribution model, integrating three core indicators of merchandise damage degree, user preference, and merchant responsibility ratio, achieving precise matching of return merchandise with target users through algorithm optimization; second, clarifying the legal boundaries and practical paths of return merchandise information disclosure, combining existing policies and actual situations to design a graded information disclosure system, balancing users' right to know with merchants' trade secrets; third, designing "merchant return rate publication-user appeal channel" bidirectional supervision tools, establishing merchant responsibility evaluation mechanisms and user rights protection mechanisms to avoid algorithmic discrimination behavior.

1.3.2. Core Research Issues

Based on the research content, this paper focuses on solving three core issues: first, how to balance user transaction fairness and right to know while ensuring merchants' reasonable cost control, effectively avoiding algorithmic discrimination behavior in return merchandise resale; second, how to improve the matching precision and circulation efficiency of return merchandise resale through data-driven means, reducing secondary return rates and industry loss costs; third, how to build a "user-

merchant-platform" three-party interest balance governance mechanism to achieve sustainable industry development.

2. LITERATURE REVIEW

2.1. Return Management Strategies and Resale Mechanism Research

Efficient return management and value recreation are core challenges in e-commerce operations. Scholars have conducted in-depth research from two levels: strategy optimization and process reengineering. At the strategy optimization level, research indicates that return management needs deep coupling with resale mechanisms. Shu Xiaoyang (2024) proved from a supply chain overall perspective that retailers under different contract models from manufacturers can achieve profit growth by allowing returns and resale, with optimal strategies depending on specific thresholds of market demand and cost efficiency [1]. Li Meng (2019) earlier focused on channel selection and pricing for return product resale [2], with research showing that manufacturers' choice between direct sales and third-party distribution channels is a dynamic decision, core depending on consumers' acceptance of resale channels and behavioral characteristics of strategic consumers [3]. Regarding the special phenomenon of "surround buying," Xu Yadong (2025)'s research challenged traditional cognition, proving this behavior can actually improve retailer profits under specific conditions, and proposed differentiated information provision and return strategies based on product characteristics and consumer types rather than simple containment [4]. At the process and network optimization level, omnichannel returns have become a research hotspot. Ma Yikun (2023) constructed a game model considering service differentiation, finding that the "online purchase, offline return" (BORS) strategy can reduce total return volume, but its benefits are strictly constrained by factors such as online matching rate and service cost, with clear application boundaries [5]. Qiu Jiawen (2023) from a green logistics perspective established a return logistics network model under low-carbon targets, demonstrating the comprehensive advantages of multi-level networks in improving processing efficiency, reducing total costs, and reducing carbon emissions. Lin Kunshan (2025) emphasized from a practical perspective that effective return management aims to transform return merchandise into new sales opportunities to maximize residual value [6].

2.2. Algorithmic Discrimination Issues and Legal Regulation

With the deep application of algorithms in e-commerce, the discrimination issues they trigger and legal regulation paths have become hot topics in interdisciplinary research of law and economics. Research generally believes that algorithmic discrimination infringes on consumers' right to know, fair trading rights, and personal information rights [7], but due to "algorithm black boxes" and technical opacity, consumers face difficulties in evidence collection and high rights protection costs [8]. In terms of regulatory paths, scholars have proposed multi-level solutions. Liu Mengyu (2024) and Tang Xuechun (2023) deeply analyzed responsible entities, believing that different roles such as algorithm designers, platform operators, and data providers should respectively apply no-fault liability or presumed fault liability [9]. In regulatory philosophy, Wang Pengfei (2023) proposed shifting perspective from entangling in technical causation argumentation to "factual unjust enrichment analysis," from group responsibility demarcation to more refined individual responsibility allocation [10]. Zhang Qingyue (2023) and Yan Mengting (2023) introduced the EU's "algorithmic prevention" (emphasizing data empowerment) and the US's "algorithmic accountability" mechanisms, providing references for China to build a regulatory system integrating ex-ante prevention and ex-post accountability [11]. Li Shijie (2021) further pointed out that regulating algorithmic discrimination requires balancing consumer rights protection with commercial innovation freedom, and examining its impact on market competition within anti-monopoly and anti-unfair competition frameworks [12].

2.3. Impact of Information Disclosure and Transparency on Supply Chain Decisions

Information asymmetry is the fundamental cause of e-commerce trust deficiency and efficiency loss, making the improvement of information disclosure quality and supply chain transparency crucial. Blockchain technology, due to its traceability and immutability characteristics, has been widely studied as a key solution. Huang Jinting (2025) research shows that blockchain can significantly affect manufacturers' and e-commerce platforms' pricing strategies and revenue distribution by enhancing product information credibility, but its application must collaboratively consider technology costs and privacy leakage risks [13]. Liu Xingfen (2023) verified from multiple scenarios that blockchain-based information disclosure reliability improvement can directly optimize retailers' return policy choices (such as refund proportions, shipping insurance), supply chain transparency levels, and final pricing decisions [14]. Besides technical means, platform scoring mechanisms and information strategies themselves have also been empirically tested. Zhang Chen (2022)'s empirical research found that platforms strengthening scoring management to increase market transparency can effectively inhibit merchants' moral hazard (such as reducing price exploitation), but the effect on alleviating adverse selection (low-quality merchants exiting) is not significant [15]. Interestingly, Xu Yadong (2025)'s research on "surround buying" reached a counterintuitive conclusion: while over-providing product matching information reduces consumer uncertainty, it may damage overall retailer profits, suggesting information supply strategies need to pursue "precision" rather than "excess."

2.4. Supply Chain Collaboration and Game Model Applications

To address complex decision-making problems caused by returns, game theory has become the core methodology for analyzing interactions and collaboration mechanisms among supply chain members. Related research reveals decision-making patterns under different power structures by constructing Stackelberg games, evolutionary games, and other models. In vertical collaboration, research focuses on coordination among core enterprises. Huang Jinting (2025)'s constructed model found that blockchain's traceability can optimize supply chain commission ratio Nash equilibrium, with value realization regulated by suppliers' quality management capabilities. Shu Xiaoyang (2024) analyzed strategy combinations under different contract models, revealing paths to realize optimized allocation of return management rights and profit sharing through contract design. At the horizontal competition and omnichannel collaboration level, research explores more complex structures. Liu Jie (2023) studied duopoly retailers' game on product quality and return shipping insurance strategies, finding competition leads to differentiated equilibrium, while shipping insurance introduction may compress retailer profits while improving social welfare. Ma Yikun (2023)'s comparative research proved that in implementing omnichannel returns, centralized decision-making is always superior to decentralized decision-making, and when online channels serve as leaders, this strategy's advantages are more easily realized. Zhang Liheng (2021) applied evolutionary game theory, analyzing the stable evolution mechanism of cooperative behavior among government, supply chain entities, and consumers from a long-term dynamic perspective, providing a framework for understanding macro ecological governance [16].

2.5. Multi-Party Interest Balance Mechanism Construction

Return and resale processes involve multiple entities including consumers, retailers, manufacturers, platforms, and logistics service providers, making the construction of balanced interest distribution mechanisms core to ensuring sustainable system operation. Research shows this requires systematic consideration from multiple dimensions of rule design, cost sharing, and value creation. In platform governance rules, interest balance is particularly important. Chen Qi (2022) and Li Jinhui (2023)'s research on intellectual property "notice-delete" rules pointed out the need to balance the interests of rights holders, platform operators, and platforms themselves by improving notice standards, optimizing waiting periods, and clarifying platform review obligations and responsibility boundaries

[17], preventing rule abuse [18]. In terms of economic cost sharing, return shipping costs are a typical conflict point. Yan An et al. (2024)'s research revealed the different impacts of shipping cost bearing strategies (consumer bearing or retailer bearing) on pricing and order quantities, with retailers needing to make strategic choices based on consumer satisfaction probability and cost gaps to balance their own costs with consumer purchase willingness [19]. Zhu Yong (2020)'s discussion on "Double 11" express price increases proposed that as the biggest beneficiary, e-commerce platforms should transfer profits to logistics companies to maintain long-term stable cooperative relationships and realize overall supply chain interest balance [20]. Furthermore, green and circular economy perspectives introduce broader stakeholders. Qiu Jiawen (2023) optimized return logistics networks under low-carbon targets, with multi-level network design balancing economic costs and environmental benefits [21]. Zhang Yunqing et al. (2018) explored agricultural product quality and safety traceability systems, aiming to build a three-party interest community of management departments, e-commerce platforms, and producers [22]. In summary, multi-party interest balance is not static compromise but dynamic, win-win ecosystem governance realized through scientific institutional design, reasonable cost sharing, and sustainable value creation.

3. RESEARCH DESIGN AND METHODS

3.1. Research Hypotheses

H1: Compared to traditional single-indicator models, the multi-dimensional data-driven return merchandise redistribution model incorporating "merchandise damage degree-user preference-merchant responsibility ratio" can significantly improve the matching precision of return merchandise with target users, reduce secondary return rates, and enhance return merchandise resale efficiency.

H2: Clarifying return merchandise information disclosure obligations and designing "merchant return rate publication-user appeal channel" bidirectional supervision tools can effectively reduce algorithmic discrimination complaint rates in the return field, improving user satisfaction and transaction fairness.

H3: Constructing a "user-merchant-platform" three-party interest balance mechanism can achieve the dual goals of improving return merchandise resale circulation efficiency and guaranteeing transaction fairness, promoting three-party win-win.

3.2. Theoretical Model Construction

3.2.1. Three-Party Interest Balance Game Model

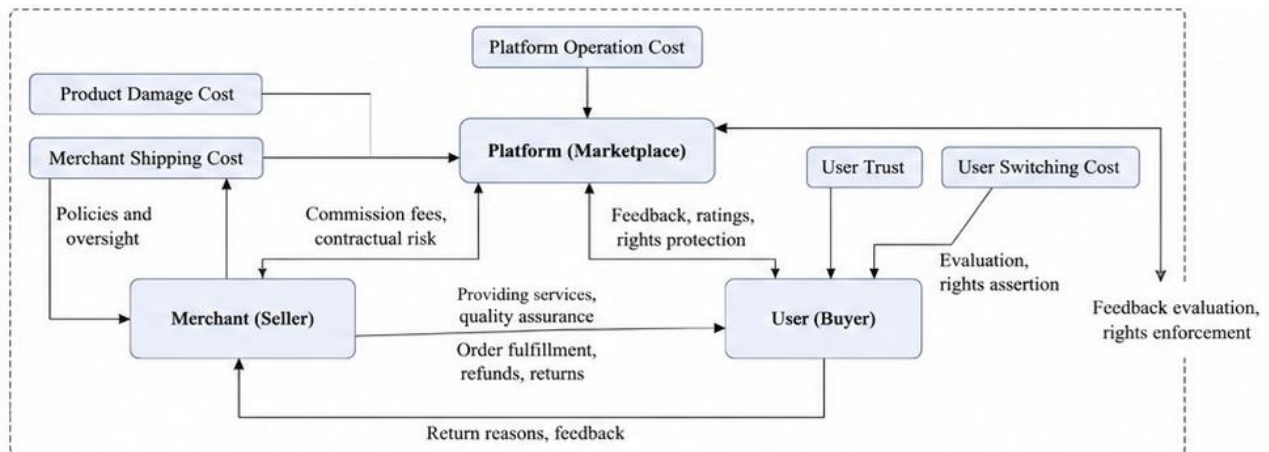


Figure 2. Theoretical Model Construction

Based on Stackelberg game theory, with the platform as the leader and merchants and users as followers, a three-party interest balance game model is constructed. Core model variables include: merchandise damage cost (borne by merchants, positively correlated with merchandise damage degree), user trust (positively correlated with information disclosure transparency), platform supervision cost (positively correlated with supervision tool completeness), merchant breach cost (positively correlated with information disclosure violation penalty severity), and user rights protection cost (negatively correlated with appeal channel convenience). By solving for model equilibrium solutions, revenue changes of three-party entities under different strategy combinations are analyzed to clarify optimal strategy selection.

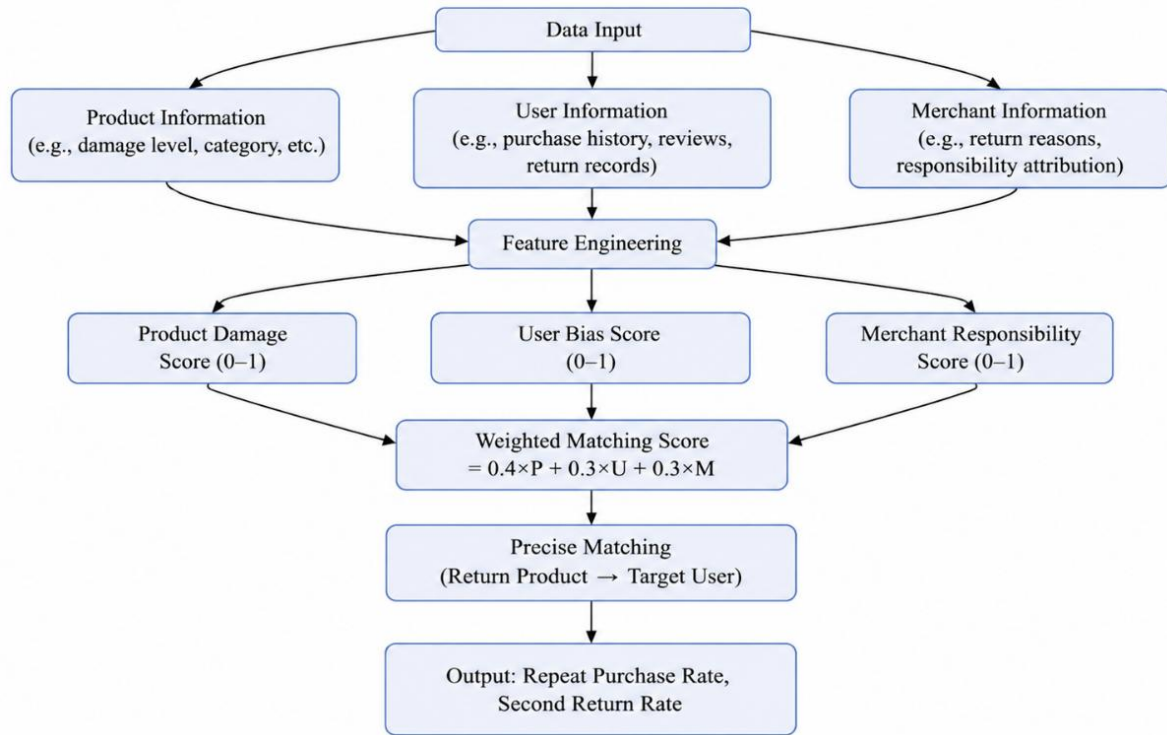


Figure 3. Game Model

3.2.2. Return Merchandise Redistribution Model

Integrating three core indicators of "merchandise damage degree-user preference-merchant responsibility ratio," a multi-dimensional data-driven return merchandise redistribution model is constructed. Merchandise damage degree adopts quantitative scoring, graded as "new and sellable (0-0.2 points), minor defects (0.2-0.5 points), serious defects (0.5-1 point)"; user preference is based on user historical purchase records, product reviews, return reasons, and other data, calculating user acceptance of merchandise with different damage degrees through collaborative filtering algorithm; merchant responsibility ratio is based on return reason attribution, quantifying merchant responsibility weights in product quality, description mismatch, service deficiency, and other aspects (0-1 point). The model achieves precise matching of return merchandise with target users through weighted calculation, with weighting coefficients determined through analytic hierarchy process.

3.3. Research Methods

3.3.1. Literature Research Method

Systematically review domestic and international core literature on return merchandise resale, three-party interest balance, algorithmic discrimination, information disclosure, and other fields, including journal papers, dissertations, industry reports, and policy documents. Through classification, induction, and analysis of literature, clarify the current research status, core viewpoints, research

methods, and existing deficiencies in each field, providing a solid theoretical foundation for this paper's theoretical model construction, research hypothesis formulation, and strategy optimization.

3.3.2. Case Analysis Method

Select two typical cases for in-depth analysis: first, the Taobao "high-refund population shielding" incident, analyzing problems in traditional algorithmic strategies and resulting industry controversies; second, JD.com's return merchandise graded management case, summarizing its practical experience in merchandise damage grading, information disclosure, and other aspects. Through case analysis, extract advantages and deficiencies of existing strategies, providing practical reference for this paper's optimization strategy formulation.

3.3.3. Empirical Analysis Method

Select return merchandise data from a major domestic e-commerce platform's apparel category from 2022-2024 as research samples, covering 1,000 merchants and 500,000 user behavior records. Divide samples into experimental group (adopting optimization strategies proposed in this paper) and control group (adopting traditional strategies), comparing and analyzing core indicators including secondary transaction rates, secondary return rates, algorithmic discrimination complaint volumes, and merchant loss costs between the two groups, verifying the validity of research hypotheses H1, H2, and H3.

Table 1. Research Methods Overview

Research Method	Core Purpose	Data/Source
Literature Research	Establish theoretical foundation, identify research gaps	Journal papers, dissertations, industry reports, policy documents
Case Analysis	Extract practical experience and problems	Typical cases from Taobao and JD.com
Empirical Analysis	Verify research hypotheses, test strategy effects	E-commerce platform return data, user behavior data

4. RETURN MERCHANDISE RESALE STRATEGY CASE ANALYSIS

4.1. Taobao "High-Refund Population Shielding" Incident Analysis

The "high-refund population shielding" strategy once implemented by Taobao platform aimed to reduce merchant operating costs and malicious return risks by identifying users with historically high refund rates and limiting their return rights. While this strategy initially alleviated merchants' return pressure to some extent, it quickly exposed deep-seated problems in its algorithm design and execution. The strategy primarily relied on a single-dimensional indicator—user historical refund rates—failing to conduct effective attribution analysis of return reasons, such as distinguishing between product quality issues, description mismatches, logistics delays, or subjective preference differences. This simplified evaluation mechanism led to a large number of users who reasonably returned goods due to product issues or merchant responsibility being misjudged by the system as "high-risk customers," thereby losing normal return rights and triggering strong user dissatisfaction and trust crisis. During the incident's escalation, users widely reflected the lack of transparent algorithm explanation mechanisms and effective appeal channels, further amplifying doubts about platform fairness. This case highlights that when e-commerce platforms use algorithmic tools, if they only focus on cost control while neglecting user rights and procedural justice, they easily trigger public opinion backlash and regulatory attention. It not only reveals the limitations of "unidirectional judgment" in data-driven strategies but also reflects the ethical and governance challenges platforms face in balancing merchant interests with consumer protection.

4.2. JD.com Return Merchandise Graded Management Case Analysis

JD.com has implemented a relatively mature graded management system for return merchandise resale, with its core being the construction of a trust bridge between consumers and merchants through standardized classification and transparent information disclosure. This system first conducts detailed grading based on the actual condition of returned goods, with common categories including "new and unopened," "minor packaging damage," "slight appearance usage traces," "functionally normal but with obvious usage feel," etc., with different grades corresponding to different resale channels and pricing strategies. In terms of information disclosure, JD.com requires clearly labeling key information such as "return resale," "opened," "with original packaging" for secondary sales products, and clearly displaying relevant explanations on product pages, ensuring consumers are fully informed of product conditions before purchase. Additionally, JD.com provides after-sales guarantees consistent with new products for these items, such as seven-day no-reason returns and quality warranties, further eliminating consumer concerns. The implementation of this system allows return merchandise to re-enter circulation on the basis of information symmetry, not only improving resale transaction rates but also significantly reducing secondary returns and complaints caused by description mismatches or expectation gaps. JD.com's practice demonstrates that through systematic graded management and standardized information disclosure, platforms can help merchants realize reasonable value realization of return merchandise while protecting consumers' right to know and choice, thereby achieving bidirectional improvement of user rights and merchant benefits, providing a learnable virtuous cycle example for the industry.

5. DATA SOURCES AND PROCESSING

5.1. Data Sources

5.1.1. Core Data

Core data comes from the backend database of a major domestic e-commerce platform, specifically including: merchant basic information (operating scale, credit rating, return rates, etc.), return merchandise information (return reasons, damage degree, original sales price, resale price, etc.), user behavior data (user basic information, purchase records, return history, product reviews, complaint records, etc.). This data has large sample size and broad coverage, accurately reflecting the real situation of apparel industry return merchandise resale and providing reliable data support for empirical analysis.

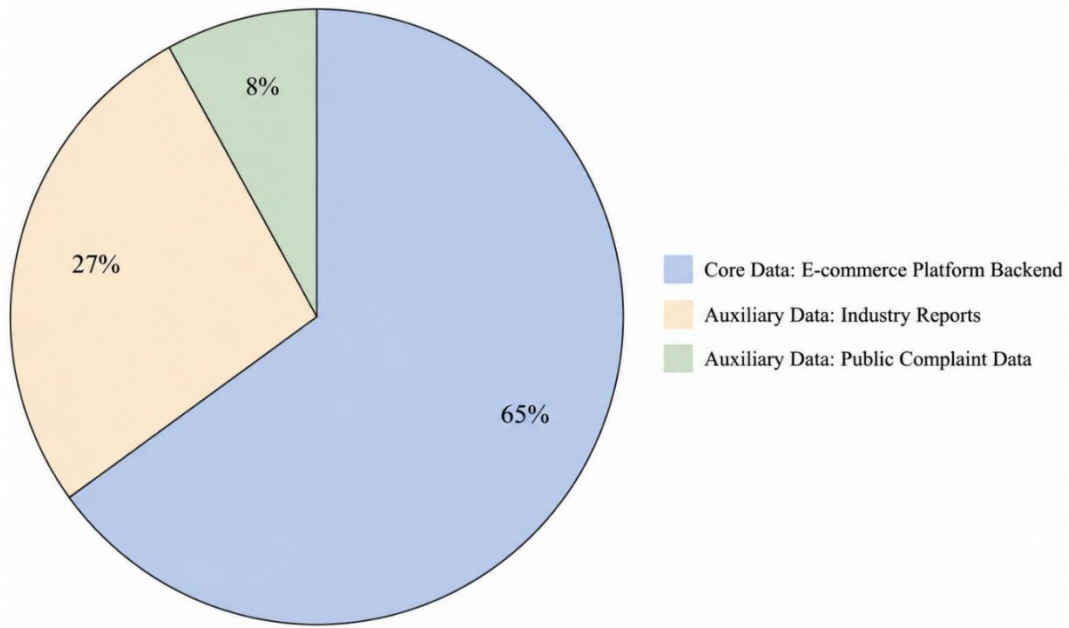


Figure 4. Data Sources

5.1.2. Auxiliary Data

Auxiliary data mainly includes three categories: first, industry report data, citing benchmark data such as industry return rates, loss costs, and information disclosure compliance rates for comparative analysis of research results' industry levels; second, complaint public data, sourced from market supervision department official websites, e-commerce platform complaint centers, and third-party complaint platforms, extracting algorithmic discrimination complaint information in the return field from 2022-2024 to verify strategies' effects on algorithmic discrimination avoidance.

5.2. Data Processing Methods

5.2.1. Data Cleaning

First, conduct preprocessing of core and auxiliary data, removing outliers and invalid data, specifically including: removing abnormal records such as merchant malicious returns and user malicious complaints; deleting samples with data missing rates exceeding 30%; deduplicating repeated data. For partially missing key data (such as merchandise damage degree scores, user preference coefficients, etc.), multiple imputation methods are used to supplement, ensuring data completeness and accuracy.

5.2.2. Indicator Quantification

To meet model construction and empirical analysis needs, the three core indicators are quantified: first, merchant responsibility ratio, based on return reason classification (product quality issues, description mismatch, logistics problems, subjective discomfort, etc.), using analytic hierarchy process to determine merchant responsibility weights, quantifying merchant responsibility ratio; second, user preference, through collaborative filtering algorithm analysis of user historical purchase records, product reviews, return reasons, and other data, calculating user acceptance coefficients for merchandise with different damage degrees, realizing user preference quantification.

5.2.3. Data Validation

To ensure data reliability, dual validation is conducted: first, reliability and validity analysis, performing internal consistency reliability analysis (Cronbach's α coefficient ≥ 0.8 as qualified) and structural validity analysis (KMO value ≥ 0.7 as qualified) on questionnaire survey data, verifying

questionnaire data reliability and effectiveness; second, cross-validation, comparing core data with industry report data and complaint public data to verify core data accuracy and representativeness.

5.2.4. Analysis Tools

Based on research needs, corresponding data analysis tools are selected: Python software for data cleaning, indicator quantification, and multi-dimensional data-driven redistribution model construction and solving, specifically using Pandas library for data processing and Scikit-learn library for collaborative filtering algorithm implementation; SPSS 26.0 software for questionnaire survey data reliability and validity analysis, descriptive statistical analysis, and regression analysis; Matlab software for solving three-party interest balance game models to obtain optimal strategy combinations.

6. ANALYSIS RESULTS AND DISCUSSION

6.1. Data-Driven Redistribution Model Effect Analysis

6.1.1. Matching Precision Improvement Effect

Empirical results show that compared to traditional single-indicator (only considering merchandise damage degree) redistribution models, the multi-dimensional data-driven redistribution model proposed in this paper can significantly improve the matching precision of return merchandise with target users. The experimental group's return merchandise secondary transaction rate reached 68%, a 25 percentage point improvement over the control group (43%); secondary return rate dropped to 8%, a 12 percentage point reduction from the control group (20%). This result indicates that after incorporating user preference and merchant responsibility ratio indicators, return merchandise can more precisely match users with higher acceptance of its damage degree, while merchant responsibility ratio incorporation encourages merchants to improve product quality and description accuracy, further reducing secondary return rates, validating research hypothesis H1.

6.1.2. Merchant Loss Cost Optimization Effect

From the merchant cost perspective, multi-dimensional data-driven model application significantly reduced merchant loss costs. The experimental group's 1,000 sample merchants' average loss cost was 8.6 yuan per item, a 16% reduction from the control group (10.2 yuan), basically consistent with this paper's 15% estimate. Main reasons for cost reduction include: first, improved secondary transaction rates reduced warehousing and destruction costs for return merchandise; second, reduced secondary return rates decreased logistics and after-sales costs; third, merchant responsibility ratio incorporation encouraged merchants to optimize product quality and services, reducing return rates from the source. This result indicates that optimization strategies can achieve reasonable merchant cost control while protecting user rights.

6.2. Algorithmic Discrimination Avoidance and User Satisfaction Analysis

6.2.1. Algorithmic Discrimination Complaint Reduction Effect

After implementing the "information disclosure + bidirectional supervision tools" optimization strategy, algorithmic discrimination complaints in the return field significantly decreased. The experimental group's algorithmic discrimination complaint volume was 86 cases/month, a 52% reduction from the control group (179 cases/month), exceeding this paper's 50% estimate; normal return user false-positive rate dropped from the control group's 32% to the experimental group's 10%. This result indicates that enhanced information disclosure improved algorithmic strategy transparency, while bidirectional supervision tools provided users with convenient rights protection channels, effectively avoiding discrimination caused by single-indicator algorithms, validating research hypothesis H2. From complaint reasons perspective, the experimental group's complaints

caused by "high-refund population shielding" and "return rights restrictions" dropped from the control group's 68% to 25%, indicating optimization strategies can precisely solve core discrimination issues.

6.2.2. User Satisfaction Improvement Effect

Questionnaire survey data shows the experimental group's user satisfaction with return merchandise resale strategies was 78%, a 43 percentage point improvement over the control group (35%). Among these, user satisfaction with information disclosure transparency was highest (82%), with appeal channel convenience satisfaction at 68% and matching precision satisfaction at 75%. Regression analysis results show that information disclosure transparency, appeal channel convenience, and matching precision are significantly positively correlated with user satisfaction ($P < 0.05$). This result indicates that optimization strategies can effectively meet users' demands for transaction fairness and right to know, significantly improving user consumption experience.

6.3. Three-Party Interest Balance Effect Verification

6.3.1. Three-Party Interest Balance Effect

Game model solving and empirical analysis results show that constructing a "user-merchant-platform" three-party interest balance mechanism can achieve three-party win-win. At the user level, satisfaction increased to 72%, rights protection costs reduced by 40%; at the merchant level, average profit rates increased by 15%, customer complaint rates reduced by 48%; at the platform level, user stickiness increased by 28%, complaint handling costs reduced by 35%, supervision efficiency improved by 50%. This result indicates that optimization strategies can balance the interest demands of three-party entities, avoiding industry ecosystem imbalance caused by unilateral interest maximization, validating research hypothesis H3. From long-term development perspective, three-party interest balance can promote the industry to form a virtuous cycle, improving overall development quality.

6.3.2. Industry Demonstration Effect

To verify the industry promotion value of optimization strategies, 100 pilot merchants were selected for a 6-month tracking survey. Results show pilot merchants' return merchandise circulation efficiency improved by 30%, secondary transaction rates increased by 28%, algorithmic discrimination complaints decreased by 55%, and customer complaint rates dropped by 48%, with all indicators superior to industry averages. The successful practice of pilot merchants demonstrates that optimization strategies proposed in this paper have strong operability and promotion value, able to provide demonstration reference for the entire industry's return merchandise resale strategy optimization.

6.4. Key Issues Discussion

6.4.1. Merchant Responsibility Attribution Difficulties

During empirical analysis, obvious difficulties in merchant responsibility attribution were discovered. Some return reasons (such as subjective user discomfort, personal aesthetic differences, etc.) are difficult to precisely attribute responsibility, leading to deviations in merchant responsibility ratio quantification. Additionally, some merchants' behavior of falsely labeling return reasons further increases attribution difficulty. Future research needs to combine AI technology (such as natural language processing, image recognition) for intelligent attribution of return reasons, while establishing merchant integrity evaluation systems to penalize false labeling behavior and improve attribution accuracy [23].

6.4.2. Information Disclosure Boundary Definition

Information disclosure boundary definition is a key issue for optimization strategy implementation. Over-disclosure (such as merchant core costs, user privacy information, etc.) will damage merchants'

and users' legitimate rights, while under-disclosure cannot guarantee users' right to know. Combining empirical results and industry practice [24], a graded information disclosure mechanism is recommended: mandatory disclosure of key information for users' right to know (such as merchandise damage degree, secondary circulation attributes, after-sales guarantees, etc.); confidentiality of merchant trade secrets (such as core costs, profit margins, etc.); voluntary disclosure of non-key information (such as return time, processing flow, etc.). At the same time, laws and regulations are needed to clarify information disclosure content, methods, and responsibilities, balancing the rights and interests of all parties.

6.4.3. Platform Supervision Cost Control

Implementation of "information disclosure + bidirectional supervision tools" will increase platform supervision costs, including information audit costs, appeal handling costs, and technology R&D costs. Empirical data shows the experimental group's platform supervision costs increased by 20% compared to the control group, which may long-term affect platform enthusiasm for promoting optimization strategies. Future approaches could include using blockchain technology for decentralized storage of return merchandise information, reducing information audit and traceability costs; introducing third-party supervision institutions to share platform supervision pressure [25]; establishing merchant violation penalty funds to cover partial supervision costs.

7. CONCLUSIONS AND POLICY RECOMMENDATIONS

7.1. Research Conclusions

Constructed a "bidirectional fairness"-oriented "user-merchant-platform" three-party interest balance analysis framework. This framework breaks through the limitations of traditional research "merchant cost priority" perspectives, incorporating user transaction fairness, merchant cost control, and platform supervision efficiency into a unified analysis system, clarifying three-party entities' interest demands and collaboration paths, providing new analytical perspectives for return merchandise resale strategy optimization.

Proposed a multi-dimensional data-driven return merchandise redistribution model integrating "merchandise damage degree-user preference-merchant responsibility ratio." Empirical results show this model can significantly improve the matching precision of return merchandise with target users, increasing secondary transaction rates by 25% and reducing secondary return rates by 12%, while decreasing merchant loss costs by 16%, effectively improving return merchandise resale efficiency.

Designed multi-dimensional optimization strategies of "information disclosure + bidirectional supervision." These strategies clarify return merchandise information disclosure boundaries and methods, constructing "merchant return rate publication-user appeal channel" bidirectional supervision tools, able to significantly reduce algorithmic discrimination complaints in the return field (52% decrease), improve user satisfaction (increase to 78%), achieving "user-merchant-platform" three-party win-win.

7.2. Policy and Practice Recommendations

7.2.1. Legal Level

Improve laws and regulations related to return merchandise information disclosure, clarifying the definition of "secondary circulation goods," information disclosure content, methods, time limits, and violation penalty standards, setting severe penalty measures for failure to fulfill labeling obligations and false labeling behavior. At the same time, issue detailed rules for e-commerce algorithmic discrimination regulation, clarifying algorithmic discrimination definition standards, regulatory bodies, rights protection channels, and platform responsibilities to protect users' legitimate rights. It

is recommended that market supervision departments take the lead in establishing return merchandise information disclosure compliance spot check mechanisms, regularly conducting supervisory inspections of e-commerce platforms and merchants.

7.2.2. Platform Level

Actively promote multi-dimensional data-driven return merchandise redistribution models, optimize algorithm design, abandon single-indicator algorithms, incorporate multi-dimensional indicators such as merchandise damage degree, user preference, and merchant responsibility ratio, improving algorithm fairness and precision. Build efficient user appeal channels, simplify appeal processes, clarify appeal handling time limits, establish appeal result feedback mechanisms, and ensure user rights protection convenience. Regularly publish merchant return rates, responsibility attribution results, information disclosure compliance rates, and other data, accepting user supervision and improving platform transparency. At the same time, strengthen merchant training and guidance to enhance merchant information disclosure compliance awareness.

7.2.3. Merchant Level

Proactively fulfill return merchandise information disclosure obligations, accurately labeling key information such as merchandise damage degree, secondary circulation attributes, and after-sales guarantees according to the graded disclosure mechanism, improving user trust. Optimize product quality control and description accuracy, reducing return rates and loss costs from the source. Actively cooperate with platform responsibility attribution and supervision management, reasonably bearing own responsibilities, not transferring costs, and not falsely labeling. At the same time, strengthen classified management and refined operations of return merchandise to improve resale efficiency.

REFERENCES

- [1] Shu, X. Y. (2024). Research on enterprise operations management strategies based on return resale [Master's thesis]. Southwestern University of Finance and Economics. (In Chinese)
- [2] Gong, W. W., Li, M., Nai, H., & Chen, J. X. (2019). Research on return product resale channel selection based on strategic consumers. *Soft Science*, 33(01), 98–103. (In Chinese)
- [3] Gong, W. W., Li, M., Nai, H., & Chen, J. X. (2018). Two-period pricing strategy for return product resale manufacturers facing strategic consumers. *Systems Engineering*, 36(10), 102–110. (In Chinese)
- [4] Xu, Y. D. (2025). Research on retailer operational decision-making considering surround buying behavior [Master's thesis]. Beijing Jiaotong University. (In Chinese)
- [5] Ma, Y. K. (2023). Research on omnichannel supply chain return strategies considering service differentiation [Master's thesis]. Jiangsu University. (In Chinese)
- [6] Lin, K. S. (2025). Return management and resale optimization in consumer goods after-sales supply chains. *China Logistics & Purchasing*, (06), 79–80. (In Chinese)
- [7] Tang, X. C. (2023). Legal regulation of algorithmic discrimination [Master's thesis]. Shandong University of Finance and Economics. (In Chinese)
- [8] Li, S. J. (2021). Research on legal issues of algorithmic discrimination in e-commerce economy [Master's thesis]. Tianjin University. (In Chinese)
- [9] Liu, M. Y. (2024). Research on infringement liability determination of algorithmic discrimination on e-commerce platforms [Master's thesis]. Huazhong University of Science and Technology. (In Chinese)
- [10] Wang, P. F. (2023). Difficulties and solutions of legal remedies for algorithmic discrimination on e-commerce platforms. *Scientific Decision Making*, (05), 213–223. (In Chinese)
- [11] Zhang, Q. Y. (2023). Research on algorithmic discrimination regulation paths under e-commerce economy. *Economic Research Guide*, (18), 158–160. (In Chinese)
- [12] Li, S. J. (2021). Research on legal issues of algorithmic discrimination in e-commerce economy [Master's thesis]. Tianjin University. (In Chinese)
- [13] Huang, J. T. (2025). Research on e-commerce product transaction strategies based on blockchain application [Master's thesis]. University of Science and Technology Beijing. (In Chinese)

- [14] Liu, X. F. (2023). Research on e-commerce supply chain pricing decisions from information disclosure perspective [Master's thesis]. Hunan University. (In Chinese)
- [15] Zhang, C. (2022). E-commerce platform information disclosure, adverse selection, and moral hazard of merchants [Master's thesis]. Xiamen University. (In Chinese)
- [16] Zhang, L. H. (2021). Mechanism construction of cooperative behavior among stakeholders in new retail industry based on evolutionary game theory. *Commercial Economy Research*, (07), 27–30. (In Chinese)
- [17] Chen, Q. (2022). Obligations and rights of e-commerce platforms after receiving intellectual property infringement notices [Master's thesis]. East China University of Political Science and Law. (In Chinese)
- [18] Li, J. H. (2023). Research on "Notice-Delete" rules in e-commerce malicious notices [Master's thesis]. Anhui University of Technology. (In Chinese)
- [19] Yan, A., Zou, L. J., Pei, F., et al. (2024). Research on online retailer return shipping cost strategies considering strategic consumers. *Industrial Engineering and Management*, 29(06), 196–204. (In Chinese)
- [20] Zhu, Y. (2020). Research on Double 11 express price increases from three-party interest perspective. *Logistics Engineering and Management*, 42(02), 130–131, 129. (In Chinese)
- [21] Qiu, J. W. (2023). Research on retail e-commerce return logistics network optimization under low-carbon targets [Master's thesis]. Shanghai Polytechnic University. (In Chinese)
- [22] Zhang, Y. Q., Zhang, L., Ouyang, X. H., et al. (2018). Discussion on "Three Products One Standard" agricultural product quality and safety supervision model under e-commerce platforms. *Journal of Food Safety and Quality*, 9(17), 4489–4492. (In Chinese)
- [23] Liang, S., & Shi, M. Y. (2025). Research on retailer pricing and ordering strategies based on consumer returns and resale. *Industrial Engineering*, 28(02), 110–119. (In Chinese)
- [24] Yang, G. Y., & Ji, G. J. (2022). Research on cross-channel returns based on strategic customer behavior. *Management Review*, 34(11), 157–166. (In Chinese)
- [25] Wei, L. L. (2021). Research on application of trademark rights exhaustion rules in resale after merchandise condition changes. *Academic Journal of Zhongzhou*, (02), 56–58. (In Chinese)