Journal of Service Science and Management, 2026, 19(1), 81-114
https://www.scirp.org/journal/jssm
ISSN Online: 1940-9907
ISSN Print: 1940-9893

From User-Generated Text to Nonlinear Demand Structures: Identifying Key Logistics Service Drivers in C2B2C Second-Hand E-Commerce

Chingkuei Kao[1]*, Guangze Chen[2], Sheng Fei[2], Zheng Zhuang[2]

[1]Key Laboratory of LNG Industry Chain, Fujian University of Technology, Fuzhou, China
[2]Department of Logistics Engineering and Management, Fujian University of Technology, Fuzhou, China
Email: *ckkao@fjut.edu.cn, zhimecz@outlook.com, feiss1224@gmail.com, 1164769600@qq.com

How to cite this paper: Kao, C. K., Chen, G. Z., Fei, S., & Zhuang, Z. (2026). From User-Generated Text to Nonlinear Demand Structures: Identifying Key Logistics Service Drivers in C2B2C Second-Hand E-Commerce. *Journal of Service Science and Management, 19,* 81-114.
https://doi.org/10.4236/jssm.2026.191005

Received: December 17, 2025
Accepted: February 21, 2026
Published: February 24, 2026

Abstract

The C2B2C model mitigates trust risks in secondhand transactions by enabling platforms to intervene deeply in logistics activities, such as pickup, inspection, delivery, and after-sales services, thereby making logistics service quality a critical determinant of user experience and platform competitiveness. However, the multinode and high-uncertainty nature of C2B2C logistics processes renders user needs more sensitive and exhibits pronounced nonlinear characteristics. Against this background, this study employs text-based corpus analysis and the Kano model to identify user demand attributes in C2B2C secondhand e-commerce logistics services. The impacts of different service elements on user satisfaction are further evaluated using Better-Worse coefficients and four-quadrant analysis. On the basis the results, four attractive logistics service demands are identified: timely pickup response, rapid return collection, flexible delivery modification, and transparent logistics information. Subsequently, the TRIZ methodology is introduced to translate these demand characteristics into actionable logistics optimization strategies. Scenario-based simulations are then conducted, combining two-proportion Z-tests and bootstrap resampling, to assess potential improvements in satisfaction following strategy implementation. Results indicate that under reasonable improvement scenarios, the proposed TRIZ-based strategies yield statistically significant or marginally significant improvements in user satisfaction across all four key logistics services. Overall, this study develops an integrated logistics service improvement and validation framework that combines corpus analysis, the Kano model, and TRIZ, providing a systematic decision-support reference for optimizing logistics operations and enhancing user experience in C2B2C secondhand e-commerce

platforms.

Keywords

Secondhand E-Commerce, C2B2C, Corpus Analysis, Logistics Service

1. Introduction

With the rise of the circular economy and increasing demand for reusing idle resources, secondhand e-commerce platforms have expanded rapidly in China, becoming a key driver of the country's circular and sustainable consumption market. Prominent examples include Goofish (Xianyu/Idle Fish), Alibaba Group's leading second-hand marketplace, and Zhuanzhuan, a major platform developed within the 58.com ecosystem and backed by Tencent. These platforms demonstrate the massive scale and mainstream adoption of secondhand e-commerce in China (Geissdoerfer et al., 2017). Goofish, originating as a C2C idle goods community, has grown into one of the largest players, while Zhuanzhuan focuses on structured trading of used items. Together, they provide a highly relevant context for studying multi-stage logistics service experiences in C2B2C (consumer-to-business-to-consumer) transactions, where individual sellers interact through platform-mediated services to reach buyers. Statistics indicate that the transaction volume of China's secondhand e-commerce market exceeded RMB 2 trillion in 2021 and is projected to reach RMB 3.8 trillion by 2025, demonstrating substantial market potential (Jing, 2025). Against this backdrop, leading platforms have gradually shifted from traditional B2C and C2C transaction models to a C2B2C e-commerce model, in which the platform intervenes in inspection, valuation, pricing, repackaging, and after-sales processing to mitigate trust risks arising from information asymmetry and quality uncertainty in secondhand transactions (Zhao et al., 2020).

However, while the C2B2C model enhances transaction credibility, it also considerably amplifies the complexity of logistics services in shaping user experience. Under this model, logistics services no longer function merely as a supporting mechanism for product delivery but instead span the entire logistics lifecycle, including doorstep pickup, transportation and transshipment, inspection and quality verification, reprocessing and resale delivery, and after-sales returns and reverse logistics. As such, logistics has become a critical foundation supporting transaction completion and platform service commitments (Yang & Yuan, 2022). Factors such as pickup responsiveness, transportation and packaging safety, logistics information transparency, and after-sales handling efficiency may directly influence users' perceptions of platform professionalism and trustworthiness (He & Lv, 2012). Although prior studies in traditional B2C e-commerce contexts have demonstrated that delivery timeliness, reliability, and information feedback capability considerably affect customer satisfaction (Chen & He, 2008), directly extending these conclusions to C2B2C secondhand e-commerce logistics remains problematic. On the one hand, C2B2C logistics processes are longer, involve more service nodes, and require coordination among more stakeholders (Sun et al., 2025); on the other hand, secondhand products are characterized by substantial variations in condition, high value volatility, and incomplete quality information (Pandey et al., 2024), which intensify uncertainty and risk perception during the logistics process. Consequently, users' attention to logistics services is no longer confined to "on-time delivery" but now spans multiple critical nodes, including pickup, inspection, resale delivery, and return handling.

Given that C2B2C secondhand e-commerce logistics involves multiple stages and service nodes, the roles of different logistics service elements in the user experience are inherently uneven, and their importance may vary substantially across contexts (Parasuraman et al., 1988; Mittal et al., 1998). If user needs are not systematically identified and stratified, evaluations based solely on overall service quality or predefined dimensions may obscure "low-salience but high-sensitivity" critical demands (Kano et al., 1984; Mikulić & Prebežac, 2011). Therefore, within the C2B2C logistics context, logistics demand must be explicitly identified, how different logistics service elements structurally influence satisfaction must be analyzed. Nevertheless, most existing logistics service quality studies rely on structured questionnaire surveys (Rashid & Rasheed, 2024), which typically assume that users can provide rational and stable post hoc evaluations based on a single service outcome. In multinode, high-uncertainty C2B2C logistics scenarios, however, user experience is often stage specific, nonlinear, and highly context dependent, and users' valid concerns and emotional responses may not be fully captured by predefined measurement scales (Olsson et al., 2023). As a result, reliance on traditional questionnaire methods alone may underestimate or misinterpret the actual effects of specific critical logistics service elements on satisfaction formation.

Given these limitations, a research perspective that more closely reflects users' real experiences must be introduced before conducting questionnaire surveys. In recent years, natural language-based corpus analysis methods have been widely applied in service quality and user experience research because they can extract high-frequency concerns and emotional responses from user-generated reviews and compensate for the limitations of traditional questionnaires in identifying latent demands (Hou et al., 2024). Systematic analysis of user reviews provides empirically grounded evidence with higher contextual validity for subsequent logistics service element selection and structured modeling. On this basis, this study introduces the Kano model to identify demand attributes of logistics service elements and thus further analyze the nonlinear effects of logistics service demands on user satisfaction. The Kano model distinguishes among must-be, one-dimensional, and attractive demands and reveals the asymmetric effects of service elements on satisfaction in their presence versus absence (Hu et al., 2022; Wachinger et al., 2023). However, traditional Kano classification relies primarily on frequency-based judgments and may not adequately capture differences in the intensity of influence on satisfaction and dissatisfaction (Li et al., 2025). Accordingly, recent studies have proposed integrating the Better-Worse coefficients and quadrant analysis to enable a more refined quantitative evaluation of demand priorities (Lu et al., 2025).

In summary, this study focuses on logistics services in C2B2C secondhand e-commerce platforms. It develops a systematic research framework that integrates user-review corpus analysis, Kano-based demand-attribute identification, quantification of the Better-Worse coefficient, and TRIZ-based strategy derivation and validation of effectiveness. The study first identifies the most sensitive logistics service dimensions and key touchpoints from users' natural language reviews; it then employs the Kano model and Better-Worse analysis to examine systematically the structural effects of different logistics service elements on user satisfaction; finally, it translates critical demands into actionable logistics optimization strategies. The findings provide theoretical support and practical guidance for C2B2C secondhand e-commerce platforms seeking to build logistics service systems with enhanced responsiveness, transparency, and credibility and contribute methodological extensions to research on logistics service quality in secondhand e-commerce contexts.

2. Literature Review

2.1. Logistics Service Characteristics and User Needs in C2B2C Second-Hand E-Commerce

In recent years, the C2B2C model, characterized by secondhand product collection, platform-based inspection, and resale, has gradually emerged as an essential form of e-commerce within the context of the circular economy (Fan, 2021; Pan, 2025; Zhang, 2025). In contrast to traditional B2C e-commerce, which is typically based on standardized products and linear delivery processes, C2B2C transactions involve secondhand goods. Each item exhibits inherent heterogeneity and cannot be fully described by uniform parameters, resulting in non-standardization, information asymmetry, and quality uncertainty (Fernando et al., 2018). Consequently, platforms are required to assume a stronger role in risk mitigation and trust intermediation during transactions (Pavlou & Gefen, 2004). Correspondingly, the logistics system in C2B2C settings becomes more complex, involves more participants, and considerably heightens users' perceived risk, thereby giving rise to logistics service demands that are more differentiated, multilayered, and highly context dependent (Rao et al., 2011).

Under the C2B2C model, logistics is no longer a one-way process of "seller shipment followed by buyer receipt" but rather a multistage system spanning the entire transaction lifecycle. This system includes doorstep pickup, inbound sorting and professional inspection, repackaging, secondary delivery, after-sales return collection and reverse logistics, and logistics tracking and exception notifications. Overall, it exhibits a closed-loop structure of "pickup-inspection-reshipment-return" (Zhao, 2020). In this context, users' attention to logistics services extends beyond delivery timeliness to encompass multiple critical service touchpoints, forming a more complex demand structure (Vakulenko et al., 2019).

First, given significant variations in product condition and incomplete historical information, users often struggle to assess the condition of secondhand goods accurately before purchase. As a result, they rely heavily on signals of safety and reliability provided by the platform through logistics-related services (Akerlof, 1970). Existing studies indicate that service touchpoints such as professional inspection, condition grading, and exception status notifications are crucial cues that users use to evaluate a platform's review capability and willingness to assume responsibility (Chen, 2024). The performance of these services directly influences users' perceptions of platform trustworthiness. Second, compared with new-product e-commerce, secondhand platforms generally experience remarkably higher return rates, driven by factors such as condition mismatch, transportation damage, and disputes over valuation or inspection outcomes (Jin, 2022). In this context, users become particularly sensitive to the logistics experience during the return process, especially regarding the timeliness of doorstep return pickup and whether abnormal situations can be proactively identified and handled. Once after-sales logistics responses are delayed or processes become cumbersome, user dissatisfaction tends to escalate rapidly, making these service elements key determinants of overall satisfaction. Moreover, the transaction value and usage experience of secondhand goods depend heavily on the preservation of condition, packaging protection, and transportation outcomes (Chen, 2024). Rather than focusing solely on delivery speed, users are more inclined to manage perceived parcel risk by relying on logistics-related information feedback, thereby reducing transaction uncertainty. Consequently, the controllability of logistics status and information transparency become critical signals of platform professionalism, with timely and transparent information often providing greater psychological reassurance than single performance indicators such as speed.

In addition, C2B2C platforms typically need to coordinate multiple actors, including in-house platform teams, third-party carriers, and crowdsourced logistics providers (Carbone et al., 2017). While such multiactor collaboration enhances capacity flexibility, it also increases the risk of inconsistent responses. As a result, delays or communication breakdowns at critical nodes such as pickup or return collection are easily interpreted by users as signs of unprofessionalism or unreliability, thereby triggering significant negative evaluations (Holloway & Beatty, 2003).

In summary, C2B2C secondhand e-commerce logistics is characterized by multistage processes, high uncertainty, and intensive reverse flows. These structural features lead to pronounced heterogeneity in user demand attributes across different service nodes. Sole reliance on predefined structured scales often fails to fully capture users' valid concerns and emotional responses in real transaction contexts. Therefore, demand cues must be extracted from users' natural language expressions to substantiate the above contextual assessments empirically, which provides a direct motivation for introducing user-generated review corpus analysis in this study.

2.2. Application of Textual Analysis Methods in Research on User Needs for E-Commerce Logistics

With the increasing complexity of platform-based services and digital transaction environments, scholars have gradually recognized that relying solely on structured questionnaire surveys is insufficient to capture users' real-time perceptions and latent needs during actual service experiences fully (Bitner et al., 2000). In recent years, text mining and corpus-based analysis methods that utilize user-generated reviews have become critical, complementary approaches in research on service quality, user experience, and platform governance (Archak et al., 2011). Prior studies suggest that the focal concerns, emotional tendencies, and high-frequency expressions revealed in users' natural-language reviews often more accurately reflect their genuine perceptions of service processes, particularly in logistics services characterized by multiple touchpoints and multistage interactions (Tirunillai & Tellis, 2014).

In e-commerce logistics, a growing body of literature has employed user review data to analyze dimensions such as delivery timeliness (Ravula, 2020), packaging safety (Esfahanian & Lee, 2022), information transparency (Wang et al., 2023b), and after-sales service (Dai et al., 2020). Compared with questionnaire-based surveys, review corpora offer advantages including contextual authenticity, spontaneous expression, and temporal continuity (Tirunillai & Tellis, 2014). These characteristics enable researchers to identify where users' attention is most frequently concentrated and which service issues are most likely to trigger emotional responses, thereby providing empirical foundations for subsequent quantitative modeling. Some studies further integrate the SERVQUAL framework to examine the applicability and limitations of traditional B2C logistics service quality dimensions in platform-based and networked contexts (Rao et al., 2011).

The applicability of corpus analysis methods is particularly pronounced in secondhand e-commerce and C2B2C settings. On the one hand, given significant variability in product condition and incomplete quality information, users are more inclined to express subjective perceptions regarding logistics safety, inspection reliability, and exception handling in their reviews (Akerlof, 1970). On the other hand, multistage processes such as door-to-door pickup, platform inspection, secondary delivery, and return recovery result in distinct, staged user experiences that are often difficult to capture comprehensively through a single-round questionnaire survey (Patrício et al., 2008). Existing research indicates that in such complex service systems, corpus analysis is an effective tool for identifying critical service touchpoints and uncovering latent demand structures (Tirunillai & Tellis, 2014).

Moreover, prior studies have shown that corpus analysis outcomes can be used to validate and complement demand classifications derived from the Kano model. Service attributes that are frequently mentioned but emotionally neutral in user reviews tend to correspond to must-be or one-dimensional needs in the Kano framework (Kano et al., 1984). By contrast, attributes with lower mention frequency but strong emotional responses are more likely to reflect potential attractive needs or opportunities for differentiated innovation (Matzler & Hinterhuber, 1998). Therefore, introducing review-based corpus analysis before questionnaire design and Kano classification not only facilitates the selection of representative logistics service attributes but also provides an external consistency check for subsequent demand attribute identification.

Based on these research advances, this study, after defining the contextual characteristics of C2B2C secondhand e-commerce logistics services, further analyzes user review corpora to examine users' logistics-related concerns during real transaction processes empirically. The results of this analysis serve as a critical foundation for the subsequent design of the Kano questionnaire and the classification of demand attributes, thereby establishing a coherent analytical linkage among contextual characterization, corpus-based validation, and demand modeling.

2.3. Kano Model and User Demand Attributes for Logistics Services

The preceding sections reveal several salient characteristics of logistics service demand in secondhand C2B2C platforms. On the one hand, the logistics process is characterized by multiple stages, high uncertainty, and a high degree of reverse flows. On the other hand, users' perceptual intensity and emotional responses to different service elements are often asymmetric. Some service elements are frequently mentioned but elicit neutral emotions, while others are mentioned less regularly yet embody substantial latent value. Under such conditions, relying solely on traditional linear satisfaction scales, where better service performance is assumed to lead to higher satisfaction and poorer performance to lower satisfaction makes it difficult to capture accurately the actual roles of different logistics service elements in shaping user satisfaction. Therefore, analytical tools capable of identifying the nonlinear characteristics of user demand are required (Liu et al., 2025).

The Kano model (Kano et al., 1984) is a well-established theoretical framework for explaining nonlinear satisfaction responses to different service attributes. It classifies user requirements into five categories: 1) must-be, 2) one-dimensional, 3) attractive, 4) indifferent, and 5) reverse attributes. A core advantage of the Kano model is its dual-question design, in which each service element is evaluated through a functional question (user perception when the service is provided) and a dysfunctional question (user perception when the service is not provided). On the basis of a standardized evaluation matrix, users' perceptions are classified into specific demand types, allowing the identification of the nonlinear effects of service attributes on satisfaction (Zhang & Wang, 2024). This feature makes the Kano model particularly suitable for platform-based services involving multiple nodes and multiple actors. In the context of C2B2C secondhand logistics, users' concerns differ substantially across stages, including doorstep pickup, platform inspection, repackaging and reshipment, and after-sales return and recovery (Zhao, 2020). This variation indicates that user perceptions of logistics services are not uniformly distributed, but rather contain service value spaces that have not yet been fully activated.

Accordingly, the integration of user-generated content analysis and the Kano model in this study is not merely a supplement to traditional service quality measurement approaches. Instead, it constitutes a targeted response to the highly uncertain and structurally complex demand characteristics of C2B2C logistics services. By identifying the demand attributes of specific logistics service elements, this approach enables a more apparent distinction between basic assurance-oriented requirements and potentially attractive requirements, thereby providing a systematic analytical foundation for subsequent Better-Worse coefficient analysis and the formulation of service optimization strategies.

3. Questionnaire Design

Before conducting the Kano questionnaire survey, this study analyzed a user review corpus as an exploratory step. By examining high-frequency keywords and sentiment tendencies, key logistics service dimensions and critical touchpoints that users are most sensitive to in the C2B2C secondhand e-commerce context were identified. This process also enabled an assessment of the coverage and perceptual differentiation of existing logistics service frameworks, thereby verifying their applicability to the C2B2C logistics system.

On the basis of the identified service dimensions and the operational characteristics of C2B2C secondhand logistics, the logistics process was systematically decomposed into measurable service elements. These elements served as the basis for constructing the Kano questionnaire items. By using the functional and dysfunctional question pairs of the Kano model, the demand attributes of each logistics service element were identified. In addition, the Better-Worse coefficients were applied to quantify the asymmetric effects of service elements on satisfaction and dissatisfaction, providing a structured empirical foundation for subsequent logistics service optimization and priority setting.

3.1. Design of Logistics Service Dimensions in the Questionnaire

To validate users' actual focal concerns under the C2B2C secondhand e-commerce logistics context characterized by multistage processes, high uncertainty, and elevated risk perception, and to provide empirical support for the subsequent selection and structuring of logistics service elements in the questionnaire, this study collected user comments on logistics services from the Goofish secondhand e-commerce platform as the primary corpus data source. A total of 1673 raw user comments were obtained via Python-based web crawling. After rigorous data cleaning and preprocessing, including removing blank and invalid entries, text normalization, duplicate elimination, and sentiment polarity annotation, 1023 valid comments were retained, yielding an effective retention rate of 61.15%.

To ensure the validity of the text analysis and the reliability of the results, a minimum character-length threshold was applied during the preprocessing stage as a key criterion for screening corpus quality. Specifically, following established practices in text mining and sentiment analysis research, comments containing fewer than 20 Chinese characters were excluded. This threshold was designed to eliminate overly short comments with limited informational value or those expressing only simple affective reactions (e.g., "perfect", "okay"), thereby ensuring that retained comments contained relatively complete service descriptions, contextual information, and evaluative content. After duplicate removal, invalid-content filtering, and length screening, all 1023 retained comments met the ≥ 20-character criterion, indicating a high degree of consistency and informational sufficiency across the corpus. This result provided a robust data foundation for subsequent keyword matching, service-dimension mapping, and sentiment polarity analysis.

An overview of sentiment distribution across the 1023 valid comments shows that 902 (88.17%) were positive, 100 (9.78%) were neutral, and only 21 (2.05%) were negative, suggesting that the platform's logistics services maintained a generally favorable reputation. However, given the lengthy process chains, complex responsibility boundaries, and heightened risk perception inherent in the C2B2C model, aggregate sentiment proportions alone are insufficient to reveal users' truly sensitive service nodes. Consequently, the latent concern structure embedded within comments must be analyzed further at the dimensional level.

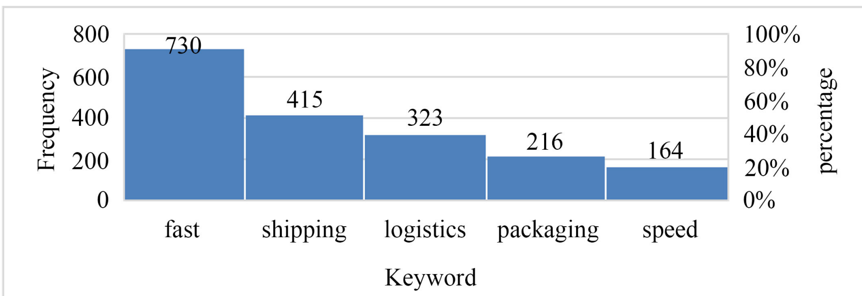

Figure 1. Frequency of high-frequency keywords.

Figure 1 summarizes the five most frequently occurring keywords in the cleaned corpus: "fast," "shipping," "logistics," "packaging," and "speed." Among them, "fast" (730 occurrences) and "speed" (164 occurrences) ranked highest, indicating strong user concern for logistics responsiveness and overall time efficiency. "Shipping" (415 occurrences) and "logistics" (323 occurrences) suggest that user evaluations extend beyond final delivery outcomes to encompass the entire logistics process, from pickup to transportation. Notably, "packaging" (216 occurrences) ranked fourth, highlighting the importance of cargo protection and integrity in secondhand e-commerce contexts. Given the variability in condition and value of secondhand goods, packaging quality directly influences users' trust in the platform's inspection professionalism and accountability. Overall, the high-frequency keyword structure in Figure 1 clearly reveals two core user concern domains: basic, rigid requirements (timeliness, shipping, logistics processes) and risk-buffering requirements (packaging and safety assurance).

Although these keywords are expressed in natural language, they are not isolated; instead, they implicitly point to users' core concerns regarding different logistics service attributes. Accordingly, this study further conducted semantic classification and dimensional mapping of the high-frequency keywords to transform raw word-frequency statistics into structured service-quality constructs. Five central logistics service dimensions were identified: responsiveness, flexibility, assurance, interaction, and transparency, as detailed below.

1) Keywords such as "fast," "shipping," and "speed" are highly concentrated within the responsiveness dimension, reflecting users' sensitivity to pickup response, shipping initiation, and delivery pace. These expressions directly correspond to evaluations of whether logistics operations are handled promptly and efficiently, representing the most explicit service demands in secondhand e-commerce logistics.

2) The keyword "packaging" clearly maps onto the assurance dimension. In secondhand commerce contexts, packaging quality not only ensures transportation safety but also serves as a critical signal of the platform's inspection professionalism and responsibility.

3) The keyword "logistics," as a broad and generalized term, encompasses multiple aspects, including delivery processes, status tracking, and overall flow experience. Its semantic meaning requires contextual interpretation and is therefore mapped jointly to the responsiveness and transparency dimensions.

4) The remaining dimensions, i.e., flexibility, interaction, and transparency, do not appear directly among the top five keywords. However, this does not imply a lack of importance. Instead, it suggests that these service attributes have not yet formed stable, explicit linguistic labels in users' spontaneous expressions and remain in a low-frequency but potentially sensitive state. This phenomenon itself reflects the high uncertainty and multistage structure of C2B2C logistics systems.

After the initial semantic mapping of keywords to service dimensions, this study further constructed the keyword–dimension association matrix shown in Figure 2, systematically mapping all 1023 high-quality comments. In this matrix, rows represent high-frequency keywords, columns represent the five logistics service dimensions, and color intensity reflects a combined measure of keyword frequency and sentiment polarity.

Figure 2 visually illustrates the concentration and emotional tendencies of keywords across service dimensions. For example, "fast," "shipping," and "speed" form highly saturated clusters within the responsiveness dimension, with strongly positive sentiment orientations (mean sentiment score > 0.75), indicating that processing speed remains the most directly perceived and evaluated aspect of multistage logistics processes. Meanwhile, keywords such as "packaging," "intact," and "safe" cluster stably within the assurance dimension, reflecting users' heightened sensitivity to cargo protection during transportation, consistent with the variability and value instability of secondhand goods.

This three-layer mapping structure, comprising keyword, dimension, and sentiment, effectively avoids the fragmentation inherent in simple word-frequency analysis, enabling natural-language user evaluations to be reconstructed into interpretable service-quality structures. At the same time, flexibility, interaction, and transparency dimensions appear as low-density "semantic cold zones" in the matrix. Rather than indicating the absence of data, this pattern suggests that these service attributes have not yet been sufficiently perceived or explicitly articulated in current platform experiences.

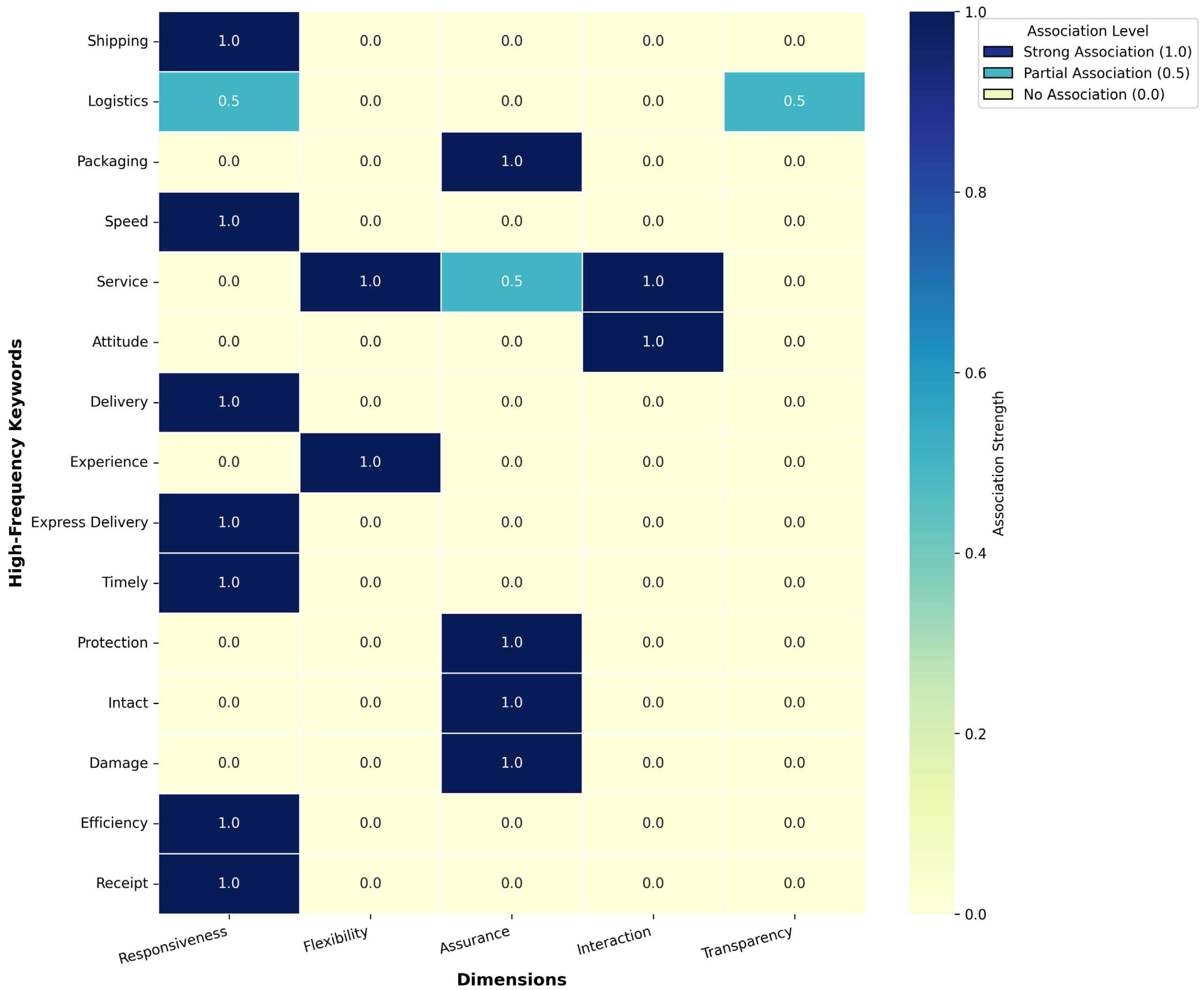

Figure 2. Keyword-dimension association matrix.

Building on the keyword–dimension associations, Figure 3 further aggregates the five service dimensions at a macro level. Two indicators are used: coverage rate, which measures how widely a service dimension is mentioned across all comments, and average sentiment score, which reflects the overall emotional orientation when that dimension is referenced. Together, these indicators provide a holistic view of users' perceptions of logistics services. The results show that responsiveness and assurance exhibit high coverage and high sentiment scores, indicating that they constitute the basic perception layer of secondhand platform logistics services. By contrast, flexibility, interaction, and transparency demonstrate low coverage but non-low sentiment scores, implying that once these services are experienced, they tend to generate favorable evaluations. However, their visibility and perceptibility remain limited.

In summary, the dimensional coverage and sentiment distribution derived from user comment analysis are highly consistent with the structural characteristics of C2B2C secondhand e-commerce logistics. Specifically, such logistics systems exhibit multistage processes, high uncertainty, and strong reverse-flow characteristics, leading users to rely heavily on platform-provided safety and controllability signals at critical nodes. Responsiveness and Assurance demonstrate high sensitivity by directly addressing users' fundamental risk-mitigation needs, such as timely pickup, reliable transportation, and secure packaging. These attributes align with basic or performance-type requirements in the C2B2C context, where service failure immediately triggers dissatisfaction.

Conversely, flexibility, interaction, and transparency exhibit a structural pattern of low visibility and weak perception, not because users deem them unimportant, but because current service provision remains insufficiently explicit or stable. This pattern reflects the high information asymmetry, value instability, and complex boundaries of responsibility inherent in secondhand transactions. Although users may not frequently mention services such as route modification, proactive exception handling, or real-time visualization, effective provision of these services has strong potential to reduce uncertainty considerably and generate satisfaction that exceeds expectations, indicating a typical attractive (excitement) demand. Therefore, the comment corpus reveals a structural dichotomy between "high sensitivity to basic services" and "low visibility of value-added services," validating a differentiated user-concern structure across logistics nodes in C2B2C secondhand e-commerce.

While the corpus analysis effectively uncovers attention distribution and emotional tendencies across logistics service dimensions, it primarily relies on frequency and sentiment polarity to capture whether users mention a service and how they feel about it. However, it remains insufficient to determine the asymmetric effects of service provision versus its absence on user satisfaction and dissatisfaction. Accordingly, this study further integrates the Kano model to identify the asymmetric impacts of logistics service elements on satisfaction and dissatisfaction systematically, thereby providing a foundation for demand attribute classification and priority determination in subsequent analysis.

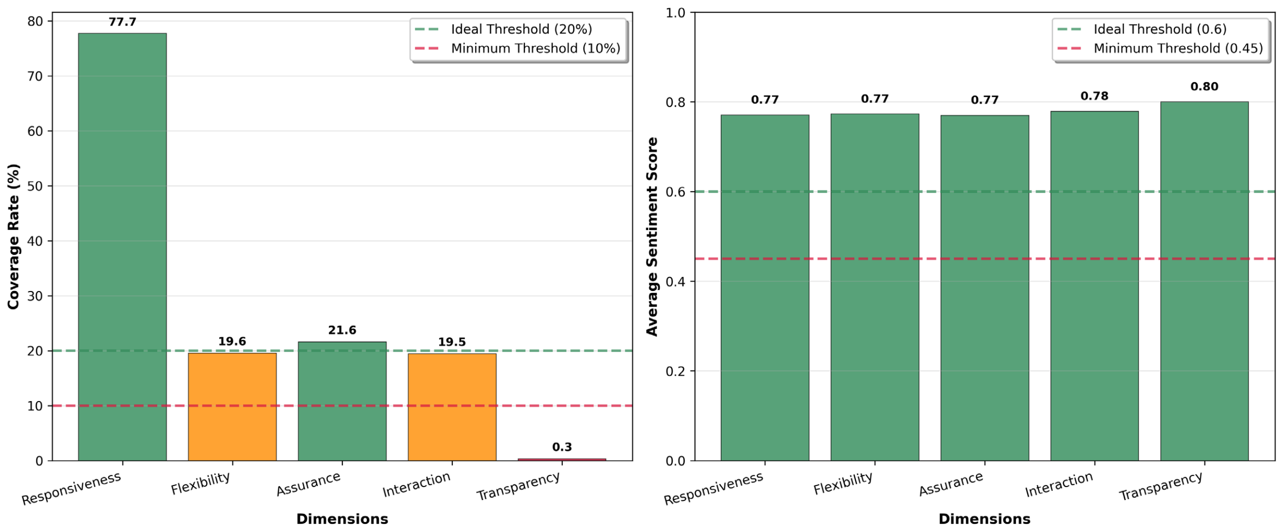

Figure 3. Dimension coverage and sentiment score.

3.2. Questionnaire Structure and Sample Characteristics

Given that logistics services in C2B2C secondhand e-commerce span multiple critical stages, including door-to-door pickup, platform inspection, repackaging, and resale delivery, and reverse logistics and returns, the user experience is not determined by a single service node but is shaped by the combined performance across multiple stages and touchpoints. Accordingly, on the basis of the five logistics service dimensions established in this study, responsiveness, assurance, flexibility, interaction, and transparency, the questionnaire was further structured to systematically identify the demand attributes of different logistics service elements and their respective roles in shaping user satisfaction.

Specifically, the questionnaire design followed a three-stage process comprising literature review, user interviews, and pilot testing. First, existing studies on C2B2C e-commerce and logistics services were systematically reviewed, and semistructured user interviews were conducted to identify representative service touchpoints, common user pain points, and latent expectations in the logistics of secondhand platforms. These insights were integrated to form an initial set of logistics service demands under the five service dimensions.

Second, drawing on the theoretical framework of the Kano model, the abstract service dimensions were further operationalized into 34 concrete and perceptible logistics service elements, around which a paired-question format was designed. Each service element was measured using a pair of questions: a functional question, capturing user perceptions when the service is provided, and a dysfunctional question, capturing perceptions when the service is not provided. This design enables the identification of users' satisfaction response patterns under different service conditions. A five-point Kano evaluation scale ("like," "expect," "neutral," "can accept," and "dislike") was adopted to guide respondents in expressing their attitudinal orientation and psychological tolerance toward each logistics service element. Rather than measuring the intensity of satisfaction, this scale emphasizes attitude types, thereby aligning with the functional-dysfunctional question structure of the Kano model. As such, it facilitates the identification of asymmetric effects of service elements on satisfaction and dissatisfaction, thereby meeting the measurement requirements for nonlinear demand attribute classification.

Before formal distribution, a pilot test was conducted to examine the clarity of item wording and the contextual appropriateness of service scenarios in the C2B2C secondhand logistics setting. On the basis of respondent feedback, minor revisions were made to improve phrasing and contextual accuracy, ensuring that each service element was mapped adequately to its corresponding service dimension. The finalized questionnaire thus maintained conceptual consistency across the five logistics service dimensions while providing a reliable empirical basis for subsequent Kano classification and Better-Worse coefficient analysis. The complete questionnaire is available at https://www.wjx.cn/vm/rXE86VL.aspx#.

The questionnaire focused on logistics service experiences in C2B2C secondhand platforms and consisted of two main sections: respondent background information and Kano demand measurement. The background section collected demographic variables such as gender, age, education level, and region, as well as respondents' roles in C2B2C transactions (buyer or seller), transaction frequency, product categories, primary platforms used, and length of platform usage. These variables were included to establish the sample's structural characteristics and to support the validity of subsequent analyses. The second section comprised the core Kano measurement items. Considering the multinode structure of the C2B2C logistics chain, the study decomposed the logistics process into 34 service elements covering pickup, transportation, inspection and evaluation, repackaging and delivery, and after-sales returns. Each component was measured using a paired set of functional and dysfunctional questions (68 items in total), enabling the capture of satisfaction and dissatisfaction mechanisms across different logistics touchpoints and supporting subsequent Better-Worse and quadrant analyses.

Formal data collection was conducted via online survey platforms, targeting individual users who had engaged in secondhand transactions and experienced the C2B2C service process within the previous six months. The survey was administered in September 2025 and distributed online through channels such as WeChat groups and secondhand trading communities on Douban. A total of 147 valid responses were collected. The sample characteristics show that 59.9% of respondents were male and 40.1% were female; users aged 19 - 30 accounted for the most significant proportion (72.8%), followed by those aged 31 - 40 (7.5%); respondents with a bachelor's degree or higher comprised 78.2% of the sample. Overall, the sample is dominated by young, well-educated users with relatively high participation in secondhand transactions, which aligns closely with the core user profile of C2B2C platforms and is broadly consistent with it, suggesting reasonable relevance to the target user segment. Although the sample characteristics align with the typical user profile of C2B2C secondhand platforms, the Kano survey sample size (n = 147) and the online convenience sampling approach imply that the empirical patterns should be interpreted primarily as reflecting the studied user segment rather than the entire consumer market. Accordingly, the Kano attribute classification and Better-Worse indices are used in this study for exploratory prioritization and mechanism interpretation under the C2B2C context, while broader market generalization requires replication with larger and more diverse samples.

4. Data Analysis

4.1. Results of Kano Attribute Classification

After collecting and screening the questionnaires, the frequencies of each service attribute classified into the five Kano categories: attractive (A), one-dimensional (O), must-be (M), indifferent (I), and reverse (R), were calculated on the basis of the Kano evaluation matrix, thereby determining the Kano attribute of each logistics service item. Subsequently, the Better-Worse satisfaction indices were computed (Zhang et al., 2024) to quantify the potential for improvement in satisfaction and the risk of dissatisfaction associated with each service element, thereby supporting the prioritization of logistics service improvements. The formulas for the Better (satisfaction) coefficient and the Worse (dissatisfaction) coefficient are shown in Equation (1) and Equation (2), respectively.

$$\text{Better} = \frac{A+O}{A+O+M+I}. \tag{1}$$

$$\text{Worse} = -\left(\frac{O+M}{A+O+M+I}\right). \tag{2}$$

In Equation (1) and Equation (2), A, O, M, I, and R represent the frequencies of the corresponding questionnaire responses. The Better coefficient indicates the maximum potential increase in user satisfaction relative to the baseline when the service is fully provided. By contrast, the absolute value of the Worse coefficient (|Worse|) reflects the degree of satisfaction loss when the service is not offered (Xiong et al., 2024). **Table 1** presents the Kano attributes and Better-Worse indices for the 34 logistics service elements of the C2B2C secondhand e-commerce platform. A Better-Worse four-quadrant matrix was constructed to illustrate the interaction between the satisfaction and dissatisfaction effects of different logistics service elements further, with Better on the vertical axis and |Worse| on the horizontal axis, using the mean values of the two indices as the dividing thresholds (Cui et al., 2025). The resulting distribution is shown in **Figure 4**. On the basis of the mean values of Better (vertical axis) and |Worse| (horizontal axis), the logistics service elements can be categorized into four quadrants with the following characteristics:

1) Quadrant I (High Better, High |Worse|): Performance-critical requirements. Representative items include Q27, Q29, Q31, Q46, Q50, Q58, Q60, Q64, Q70, and Q78. These services simultaneously exhibit strong satisfaction-enhancing potential (high Better) and a high risk of dissatisfaction if unmet (high |Worse|), such

as inspection transparency, after-sales handling, fair charging, and security assurance. These elements constitute the core factors for enhancing platform reliability and reducing disputes and should therefore be prioritized for resource allocation in the C2B2C model.

2) Quadrant II (High Better, Low |Worse|): Attractive requirements with differentiation potential. This quadrant contains a limited number of items (e.g., Q11, Q48, Q54, Q66) but holds substantial strategic value. Specifically, Q11 refers to timely response to pickup requests, Q48 to rapid door-to-door return collection, Q54 to flexible modification of delivery time and address during transit, and Q66 to real-time logistics status notifications via the app. These services share a common characteristic of information responsiveness and flexibility. When provided, they can generate unexpectedly high satisfaction gains, while their absence does not trigger strong dissatisfaction. In highly homogenized platform competition, such attractive requirements serve as critical levers for experience differentiation and repeat purchase enhancement.

Table 1. Analysis result of kano.

Service Elements	A	O	M	I	R
1. Timely response to pickup requests (Q11)	28	19	9	72	1
2. Confirmation of pickup time and personnel arrangement (Q13)	25	20	13	72	0
3. Handling temporary pickup change requests (Q15)	21	23	12	76	1
4. Completion of inspection and grading within the specified time (Q17)	19	22	9	79	1
5. Flexible scheduling of pickup and delivery time options (Q19)	24	22	7	78	1
6. Matching pickup vehicles according to shipment volume (Q21)	21	18	4	86	2
7. Provision of multiple delivery speed options (Q23)	14	16	3	95	4
8. Authentication and condition assessment services (Q25)	17	24	5	79	2
9. Safety inspection and protective packaging guidelines (Q27)	22	27	6	73	2
10. Tamper-proof and anti-counterfeiting seals at outbound shipment (Q29)	22	24	10	70	3
11. Provision of additional protective advice or materials (Q31)	21	32	8	65	3
12. Confirmation of transportation preferences before shipment (Q33)	17	18	7	89	3
13. Guidance on labeling and packaging procedures (Q35)	19	17	4	90	2
14. Display of detailed product condition information before transaction (Q37)	14	28	7	76	2
15. Disclosure of pickup lead time and pricing standards (Q39)	22	19	6	81	4
16. Transparency of inspection criteria and pricing impact (Q41)	23	22	5	80	2
17. Reasonableness of logistics service pricing (Q43)	19	26	7	77	1
18. Real-time handling of issues during the delivery process (Q46)	32	25	6	67	2
19. Prompt response to doorstep return pickup requests (Q48)	27	22	5	76	2
20. Proactive notification and resolution of logistics exceptions (Q50)	24	34	6	65	4
21. Ability to modify delivery time after seller shipment (Q52)	22	23	4	80	2
22. Allowing address modification during delivery (Q54)	25	22	2	80	2

Continued

23. Provision of multiple return processing options (Q56)	15	24	7	82	3
24. Measures to prevent condition deterioration during warehousing and transshipment (Q58)	28	30	2	66	4
25. Full-process tracking and security for high-value items (Q60)	22	33	6	69	1
26. Transparency in transshipment and vehicle handover procedures (Q62)	23	22	4	82	3
27. Maintenance of tamper-proof seals during return handling (Q64)	22	35	5	71	0
28. App-based real-time logistics location notifications (Q66)	32	22	2	78	0
29. Proactive customer service updates on return progress (Q68)	24	19	6	81	2
30. Timely coordination and resolution of after-sales disputes (Q70)	34	31	4	62	1
31. Availability of instant online customer service intervention (Q72)	20	26	7	76	3
32. Access to logistics records for each process stage on the order page (Q74)	20	19	6	86	1
33. Recording of environmental changes during transportation (Q76)	22	21	5	83	2
34. Transparency of after-sales deduction reasons (Q78)	15	40	23	53	1

3) Quadrant III (Low Better, Low |Worse|): Low-sensitivity services. Examples include Q23 (delivery option selection), Q41 (transparency of inspection-based pricing), and Q74 (order trajectory records). These services neither considerably drive satisfaction nor cause pronounced dissatisfaction when absent in the current secondhand e-commerce environment. Platforms may consider gradual optimization of these elements depending on resource availability and target user segments.

4) Quadrant IV (Low Better, High |Worse|): Must-be requirements. This quadrant includes items such as Q17 (inspection completion within the specified timeframe), Q43 (reasonableness of logistics fees), and Q56 (return handling procedures). These services represent the fundamental baseline expectations of users in the C2B2C platform. Any failure in these areas is likely to result in dissatisfaction, while satisfactory performance does not yield additional delight. Consequently, they are essential "error-intolerant" services that must be consistently maintained.

4.2. Analysis of User Demand Structure

By integrating the Kano classification results in **Table 1** with the Better-Worse quadrant distribution shown in **Figure 4**, the user demand structure of logistics services on C2B2C secondhand platforms can be summarized into two core categories: 1) salient critical demands represented by the first quadrant and 2) attractive innovation-oriented demands reflected in the second quadrant. These two categories correspond respectively to users' fundamental expectations of transactional security and trustworthiness and to their higher-level pursuit of experience enhancement, jointly forming the logical basis for platform-level logistics optimization strategies.

The first quadrant primarily focuses on process nodes closely related to transaction credibility, including inspection transparency, packaging safety, after-sales dispute handling, and cost transparency. These service elements exhibit high Better and high |Worse| values, indicating that strengthening such services can substantially improve user satisfaction. By contrast, any failure or instability is likely to trigger strong dissatisfaction. This structural characteristic aligns closely with the intrinsic nature of C2B2C transactions. Given the heterogeneity of secondhand goods in terms of condition, source, and valuation mechanisms, users rely heavily on the platform's "guarantor role" within the logistics chain. Consequently, these logistics processes become critical points for risk mitigation and naturally evolve into salient trust-sensitive touchpoints in users' evaluations.

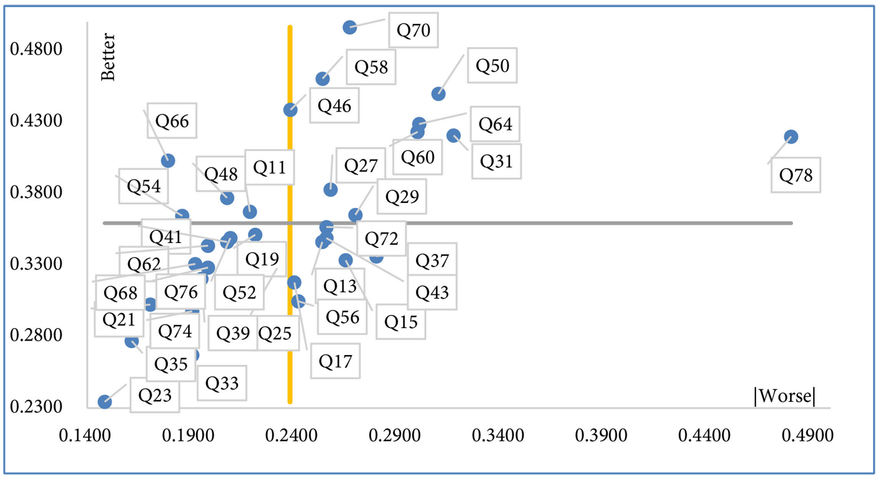

Figure 4. Better-Worse four-quadrant plot.

By contrast, the attractive demands located in the second quadrant, such as timely pickup response, flexible modification during delivery, and real-time logistics notifications, reflect users' higher-order expectations regarding information controllability, process flexibility, and service proactiveness. When effectively implemented, these services can generate satisfaction gains that considerably exceed user expectations; however, their absence does not immediately lead to pronounced dissatisfaction. As such, these demands represent key sources for enhancing user experience and differentiating platform services, and they constitute strategically valuable directions for future innovation and competition.

At a deeper level, the formation of this demand structure is rooted in the high uncertainty and information asymmetry inherent in secondhand transactions. Factors such as difficulty in fully verifying product condition, interpretive ambiguity in inspection standards, and the relatively high cost of return logistics heighten users' sensitivity to logistics as an external trust-substitution mechanism. Services related to inspection transparency, standardized packaging, antitampering measures, and return integrity therefore become essential foundations for ensuring transaction security and clarifying responsibility boundaries. Once instability occurs in these links, user satisfaction is likely to decline sharply.

Meanwhile, this study also finds that specific demands traditionally regarded as critical in conventional e-commerce, such as delivery speed preferences and shipping cost levels, do not fall into the high-impact quadrants in Figure 4. This observation is closely related to the nonessential and low-frequency nature of secondhand transactions. Users tend to exhibit relatively higher tolerance toward speed and pricing, while being extremely sensitive to issues of trust, safety, and perceived exploitation. In other words, the satisfaction structure in the C2B2C context shifts from an efficiency-oriented logic toward a trust-oriented logic. Accordingly, the core logistics task is no longer rapid delivery but rather reducing uncertainty, minimizing information gaps, and enhancing process transparency.

Overall, logistics user demand on secondhand platforms demonstrates a distinctive dual-layer structure: a foundational layer of trust-related requirements that must not fail (first quadrant), and an upper layer of experience-enhancing services capable of creating delight and differentiation (second quadrant).

5. TRIZ-Based Strategy Development and Evaluation

Based on the results of the Kano classification, the Better-Worse indices, and the four-quadrant analysis, this study finds that the most remarkable improvement potential in C2B2C secondhand e-commerce logistics services does not lie in the basic services most frequently mentioned by users, but rather in a limited number of attractive and innovative demands that can remarkably enhance user experience when fulfilled. These demands are often not explicitly articulated by users; however, once effectively provided by the platform, they can substantially increase user satisfaction and trust, thereby serving as critical leverage points for service differentiation and uncertainty reduction.

Nevertheless, such attractive demands are frequently accompanied by constraints on resource investment, process complexity, or system stability, giving rise to typical contradictions such as "service enhancement versus operational cost" or "flexibility versus efficiency." The TRIZ methodology offers a structured approach for transforming user demands into engineering parameters and systemic contradictions and for subsequently deriving innovative solutions through contradiction analysis.

Accordingly, this study adopts the key attractive logistics service demands identified through the Kano model as inputs for TRIZ-based problem modeling. By constructing the corresponding contradiction matrices, targeted optimization strategies are systematically derived to address the inherent trade-offs in C2B2C logistics service design.

5.1. Strategy Development

The strategy development focuses on four key attractive attributes (Q11, Q48, Q54, and Q66) identified through the Kano analysis. Following the TRIZ contradiction analysis procedure, this study formulates operational and innovative logistics service strategies for each attribute. The details are presented as follows:

1) Q11. Timely response to pickup requests: trade-off between efficiency and cost in C2B2C logistics

In the C2B2C model, seller-initiated doorstep pickup constitutes the starting point of the logistics chain. However, current dispatching processes typically involve coordination among in-house teams, contracted courier companies, and crowdsourced drivers. To maximize capacity utilization and reduce collection costs, platforms often rely on route-based or bundled pickups as default strategies. As a result, sellers may experience long and uncertain waiting times between request submission and actual pickup.

Although platforms usually display estimated pickup times, rigid dispatching rules and complex coordination mechanisms often lead to delays or missed appointments, undermining users' perceptions of platform professionalism and service reliability. Attempts to improve responsiveness by increasing manpower or narrowing time windows may result in idle capacity and higher subsidy expenditures, creating a clear trade-off between efficiency improvement and cost control.

Accordingly, "timely response" is abstracted as the TRIZ improving parameter "25. Time Waste," while the increased resource input required to enhance responsiveness corresponds to the worsening parameter "22. Loss of Energy/Increased Cost."

Based on the TRIZ contradiction matrix, relevant inventive principles include Principle 10 (Prior Action) and Principle 5 (Merging), as well as Principles 18 (Mechanical Vibration) and 32 (Color Change). This study primarily adopts Principles 10 and 5 to formulate two main strategic directions. The prior action strategy involves establishing pickup demand forecasting models, implementing regional predispatch mechanisms, and introducing semiappointment-based time windows, thereby shifting from passive dispatching to proactive preparation. The merging strategy consolidates multiple pickup requests within the same community or adjacent areas into unified collection routes, reducing redundant dispatches and empty mileage. Visual cues such as color codes or labels may further be used to indicate urgency levels and enhance dispatching accuracy (Wang et al., 2023a). These strategies improve responsiveness without substantially increasing capacity or operational costs, aligning well with the economic and flexibility requirements of the C2B2C context.

2) Q48. Delayed doorstep return pickup: trade-off between time waste and system complexity

Returns are highly sensitive in secondhand e-commerce contexts, and users' waiting experiences during after-sales processes often determine their continued platform usage. Given the need to coordinate in-house resources, third-party pickup agents, and courier companies, return pickups are frequently scheduled during fixed time slots or bundled with other routes, resulting in prolonged waiting times and negatively affecting users' perceptions of after-sales efficiency and platform credibility. In this case, the improving parameter is defined as "25. Time Waste," while introducing additional rules, interfaces, or prescheduling mechanisms would remarkably increase operational complexity, corresponding to the worsening parameter "36. Device Complexity."

The TRIZ principle applicable to this contradiction is Principle 6 (Universality): using shared return-backlog data, coordinated route planning across platforms and logistics providers, and reserving pickup windows in advance. Accordingly, strategic solutions may include advanced planning for return peaks, integration of carrier routes, and the establishment of dedicated return channels or fast-track recovery mechanisms to reduce waiting times without excessively increasing system complexity.

3) Q54. Allowing modifications to delivery time and address during transit: trade-off between adaptability and control complexity

Secondhand platform delivery systems typically rely on fixed routes, predictable trunk transportation, and standardized last-mile operations. Consequently, in-transit modifications often require manual intervention and are considered difficult or infeasible. Failed modifications may lead to repeated delivery attempts, delays, or return-and-reship scenarios, considerably reducing user experience (Zhu et al., 2024). In this study, the improving parameter is defined as "35. Adaptability," reflecting the system's ability to respond flexibly to users' temporary change requests. The corresponding worsening parameter is "36. Device Complexity," as increased flexibility inevitably introduces additional rules, decision branches, and coordination challenges.

The TRIZ contradiction matrix recommends Principle 15 (Dynamization), allowing real-time adjustment of routes and time slots; and Principle 28 (Replacement of mechanical system), moving from unstructured to structured. Based on these principles, strategies may include setting modification deadlines before parcels enter the last-mile stage, introducing intelligent route reconfiguration modules, and granting users a limited number of controlled modification opportunities.

4) Q66. Real-time app-based logistics location notifications: trade-off between transparency and notification burden

When logistics updates are delayed or vague, users may experience anxiety due to information gaps, which in turn increases customer service inquiries and complaint rates (Gao & Sun, 2024). Therefore, the improving parameter is defined as "24. Loss of Information," to reduce perceived uncertainty. However, persistent notifications may disrupt users and create annoyance, corresponding to the worsening parameter "31. Harmful Side Effects."

Relevant TRIZ principles include Principle 21 (Reduce harmful effects), such as using personalized push notifications and controlling push frequency; and Principle 22 (Turn harmful effects into beneficial effects), establishing early-warning notifications. Accordingly, strategic solutions may involve hierarchical notification systems, enhanced visualization of critical nodes, and proactive alerts for abnormal events, rather than simply increasing notification frequency.

In summary, this study develops targeted innovation strategies for four key attractive demands (Q11, Q48, Q54, and Q66) that address user-sensitive areas, including response speed, return efficiency, delivery flexibility, and information transparency. A consolidated overview of these strategies is provided in Table 2.

Table 2. TRIZ improvement strategy.

Key issue	Improving parameter	Worsening parameter	Innovation principle	Strategy
Q11	25. Time Waste	22. Loss of Energy/Increased Cost	5. Merging 10. Prior Action	S1. Establish a pickup peak prediction model, implement region-based pre-dispatch mechanisms, and adopt semi-appointment time windows to shift from passive order assignment to proactive preparation. In addition, consolidate pickup orders within the same area to shorten sellers' waiting time while maintaining cost efficiency.
Q48	25. Time Waste	36. Device Complexity	6. Universality	S2. Develop advanced planning for return pickup peaks, integrate carrier routing resources, and establish dedicated return routes or fast-track recovery channels to reduce waiting time without excessively increasing system complexity.
Q54	35. Adaptability	36. Device Complexity	15. Dynamization 28. Replacement of mechanical system	S3. Define modification cut-off points based on order status and transportation stage, introduce intelligent route reconfiguration modules, and allow users a limited number of controlled modification opportunities. This approach enhances flexibility for in-transit changes while keeping delivery process complexity under control.
Q66	24. Loss of Information	31. Harmful Side Effects	21. Reduce harmful effects 22. Turn harmful effects into beneficial effects	S4. Preconfigure personalized notification strategies at the time of order creation, such as tiered intelligent notifications, enhanced visualization at key milestones, and proactive alerts for abnormal events, rather than merely increasing notification frequency.

5.2. Simulation-Based Assessment of the Potential Effectiveness of TRIZ Strategies

To examine the potential effectiveness of the logistics service optimization strategies derived from TRIZ in the C2B2C secondhand e-commerce context, this study focuses on four attractive service attributes (Q11, Q48, Q54, and Q66). Because only one-round pre-implementation survey data are available (Table 1), the following analysis is designed as a scenario-based simulation rather than an empirical post-implementation verification. Specifically, using the Kano classifications and Better–Worse coefficients as the baseline, we construct hypothetical post-implementation satisfaction scenarios and evaluate whether assumed improvements could yield statistically distinguishable changes under different improvement magnitudes.

Given that only one-round preimplementation survey data were available (Table 1), this study adopts a scenario-based simulation and statistical testing approach. Specifically, using the existing Kano classifications and Better-Worse coefficients as the baseline, hypothetical postimplementation satisfaction scenarios $p_k^{(1)}$ were constructed. Z-tests and bootstrap resampling were then applied to assess whether statistically significant improvements in satisfaction could be achieved across different improvement magnitudes.

In this study, "user satisfaction with a logistics service attribute" is defined as follows: if the Kano response for that attribute is classified as A or O, it is regarded as a "positive satisfaction response;" other categories (M, I, R) are treated as "nonsatisfied or neutral responses." Accordingly, using the A, O, M, I, and R frequencies in Table 1, the baseline satisfaction proportion before TRIZ implementation can be calculated using Equation (3).

$$p_k^{(0)} = \frac{A_k + O_k}{A_k + O_k + M_k + I_k + R_k}, \quad k \in \{11,\ 48,\ 54,\ 66\} \tag{3}$$

In Equation (3), $p_k^{(0)}$ represents the probability that users are satisfied with service attribute k under the existing C2B2C logistics process. Based on Table 1, the baseline satisfaction probabilities are $p_{11}^{(0)} = 47/129 = 0.3643$, $p_{48}^{(0)} = 49/132 = 0.3712$, $p_{54}^{(0)} = 47/131 = 0.3588$, and $p_{66}^{(0)} = 54/134 = 0.4030$. Hypothetical postimplementation satisfaction proportions were constructed to assess the potential improvement brought about by TRIZ strategies, as shown in Equation (4).

$$p_k^{(1)} = \min\left(p_k^{(0)} + \Delta_k,\ 1\right). \tag{4}$$

On the basis of Equation (4), three satisfaction improvement scenarios were defined:

1) $\Delta_k = 0.05$ (mild improvement scenario): This scenario represents limited operational improvement or partial implementation of TRIZ strategies. It corresponds to situations in which TRIZ principles are applied only to localized processes (e.g., pilot implementations of proactive dispatching in selected regions), with short implementation periods or constrained organizational adjustments. Under this scenario, the analysis tests whether TRIZ strategies can generate small but detectable improvements. If statistical significance is achieved even at $\Delta_k =$ 0.05, the strategy is considered highly sensitive and broadly applicable.

2) $\Delta_k = 0.10$ (moderate improvement scenario): This scenario reflects relatively complete implementation of TRIZ strategies with more noticeable process optimization effects. It represents a typical improvement magnitude in real-world operations, such as after system upgrades (e.g., route prediction or dynamic modification modules), improved coordination among platforms, carriers, and couriers, or when users can clearly perceive service enhancements (e.g., increased delivery flexibility or improved information transparency). In service quality research, satisfaction improvements of 8% - 12% are generally considered practically meaningful.

3) $\Delta_k = 0.15$ (significant improvement scenario): This scenario corresponds to full-scale implementation and high-level integration of TRIZ strategies. It applies when platforms comprehensively deploy all four strategies (S1 - S4), achieve substantial automation upgrades (e.g., automated dispatching, intelligent return routing, optimized real-time notifications), or deliver strongly perceptible improvements in user experience. This scenario simulates the upper-bound potential and marginal effects of TRIZ strategies.

These three scenarios were designed to simulate different degrees of improvement in satisfaction following TRIZ implementation, aiming to test the statistical significance and robustness of strategy effects under mild, moderate, and remarkable improvement conditions. They correspond to partial optimization, routine improvement, and full deployment in practice, enabling an assessment of the potential effectiveness range and elasticity of improvement across different service touchpoints.

Under the assumption that the sample size n_k and questionnaire structure remain unchanged (i.e., $n_k = A_k + O_k + M_k + I_k + R_k$), the postimplementation satisfied sample size is modeled as a binomial distribution: $X_k^{(1)} \sim \text{Binomial}\left(n_k, p_k^{(1)}\right)$. This distribution allows the generation of simulated "post-test" data for statistical testing. Using the simulated data, a two-proportion Z-test was applied to compare satisfaction proportions before and after TRIZ implementation for each service attribute. For service attribute k, let the pretest satisfaction proportion be $\hat{p}_k^{(0)} = \hat{x}_k^{(0)} / n_k^{(0)}$ and the simulated post-test satisfaction proportion be $\hat{p}_k^{(1)} = \hat{x}_k^{(1)} / n_k^{(1)}$, where $\hat{x}_k^{(0)}$ and $\hat{x}_k^{(1)}$ denote the pretest and simulated post-test satisfied sample counts, respectively. Under the assumptions of independent samples and large-sample approximation, the Z statistic is calculated as shown in Equation (5), where the pooled proportion $\hat{p}_k^{\text{pool}}$ is defined in Equation (6) accordingly.

$$Z_k = \frac{p_k^{(1)} - p_k^{(0)}}{\sqrt{\hat{p}_k^{\text{pool}}\left(1 - \hat{p}_k^{\text{pool}}\right)\left(\frac{1}{n_k^{(0)}} + \frac{1}{n_k^{(1)}}\right)}}. \tag{5}$$

$$\hat{p}_k^{\text{pool}} = \frac{\hat{x}_k^{(0)} + \hat{x}_k^{(1)}}{n_k^{(0)} + n_k^{(1)}}. \tag{6}$$

If $|Z_k|$ exceeds the critical value of the normal distribution at a given significance level (e.g., $\alpha = 0.05$), the improvement effect of the TRIZ strategy on service k is considered statistically significant. By calculating Z-values and p-values for Q11, Q48, Q54, and Q66, this approach not only tests the effectiveness of individual strategies but also enables comparison of marginal benefits across different service scenarios.

To reduce potential bias arising from normal approximation and single-sample partitioning, this study further applies bootstrap resampling to verify the robustness of satisfaction improvement effects. Specifically, on the basis of binary satisfaction/nonsatisfaction responses before and after TRIZ implementation, 100,000 resamples with replacement were drawn from the pretest sample ($\text{Binomial}\left(n_k, p_k^{(0)}\right)$) and the post-test sample ($\text{Binomial}\left(n_k, p_k^{(1)}\right)$). For each resample, the proportion difference

($\Delta\hat{p}_k^{(b)} = \hat{p}_k^{(1,b)} - \hat{p}_k^{(0,b)}$) was calculated, yielding an empirical distribution of improvement effects. A 95% confidence interval was then constructed. If the interval does not include zero and the distribution is right skewed, the improvement effect is considered statistically and practically supported.

Table 3 summarizes the Z-test and Bootstrap resampling results for the four attractive services (Q11, Q48, Q54, Q66) under the three improvement scenarios (Δ_k = 0.05, 0.10, 0.15), reflecting the potential magnitude and statistical significance of satisfaction improvements if TRIZ strategies were implemented in the logistics processes of the C2B2C secondhand platform. Overall, the results demonstrate that even without postimplementation survey data, this study can construct a replicable, quantifiable framework for evaluating the effectiveness of TRIZ strategies in C2B2C logistics contexts, based on baseline satisfaction attributes from Table 1.

Table 3. Results of Z-test and bootstrap simulation.

Δ_k	Item	n_k	$\hat{x}_k^{(0)}$	$\hat{x}_k^{(1)}$	$\hat{p}_k^{(0)}$	$\hat{p}_k^{(1)}$	Z-test	P-value	Bootstrap 95% CI	
									Upper limit	Lower limit
0.05	Q11	129	47	43	0.3643	0.3333	−0.5225	0.6013	−0.1473	0.0853
	Q48	132	49	57	0.3712	0.4318	1.0044	0.3152	−0.0530	0.1818
	Q54	131	47	52	0.3588	0.3970	0.6371	0.5241	−0.0763	0.1527
	Q66	134	54	63	0.4030	0.4702	1.1085	0.2677	−0.0522	0.1866
0.10	Q11	129	47	59	0.3643	0.4574	1.5185	0.1289	−0.0233	0.2093
	Q48	132	49	65	0.3712	0.4924	1.9880	0.0468	0.0000	0.2349
	Q54	131	47	64	0.3588	0.4886	2.1254	0.0336	0.0076	0.2519
	Q66	134	54	72	0.4030	0.5373	2.2030	0.0276	0.0149	0.2537
0.15	Q11	129	47	68	0.3643	0.5271	2.6303	0.0085	0.0465	0.2791
	Q48	132	49	73	0.3712	0.5530	2.9627	0.0030	0.0606	0.2955
	Q54	131	47	70	0.3588	0.5344	2.8583	0.0043	0.0534	0.2901
	Q66	134	54	79	0.4030	0.5896	3.0543	0.0023	0.0672	0.3060

To illustrate the uncertainty intervals and stability of satisfaction improvements under different scenarios visually, Figures 5-7 present the bootstrap 95% confidence intervals of satisfaction proportion differences ($\Delta\hat{p}_k^{(b)}$) for the four attractive services under Δ_k = 0.05, 0.10, and 0.15, respectively. As shown in Figure 5, under the mild improvement scenario (Δ_k = 0.05), most confidence intervals span zero, indicating that small-scale strategy improvements are insufficient to produce stable statistically significant effects, although potential improvement trends are observable. When the improvement magnitude increases to the moderate scenario (Δ_k = 0.10), Figure 6 shows that confidence intervals for some service attributes shift toward the positive range. In particular, "delivery modification during transit" (Q54) and "logistics information push" (Q66) exhibit lower confidence bounds exceeding zero, consistent with the Z-test results in Table 3. This result indicates that TRIZ strategies related to information flexibility and transparency show robust potential for improvement under moderate implementation intensity. Under the significant improvement scenario ($\Delta_k = 0.15$), Figure 7 shows that the bootstrap 95% confidence intervals for all four attractive services fall entirely within the positive range, indicating that satisfaction improvements are not only statistically significant but also stable under resampling. This result further suggests that when TRIZ strategies are systematically implemented at the levels of process design, information mechanisms, and decision responsiveness, their improvement effects in multinode, high-uncertainty C2B2C logistics systems are structurally amplified.

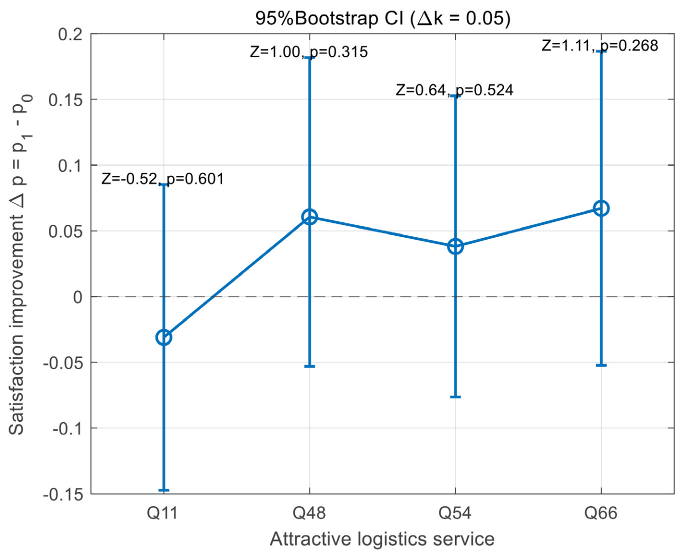

Figure 5. Bootstrap 95% confidence intervals of satisfaction proportion differences for four key attractive logistics services after TRIZ implementation when $\Delta_k = 0.05$.

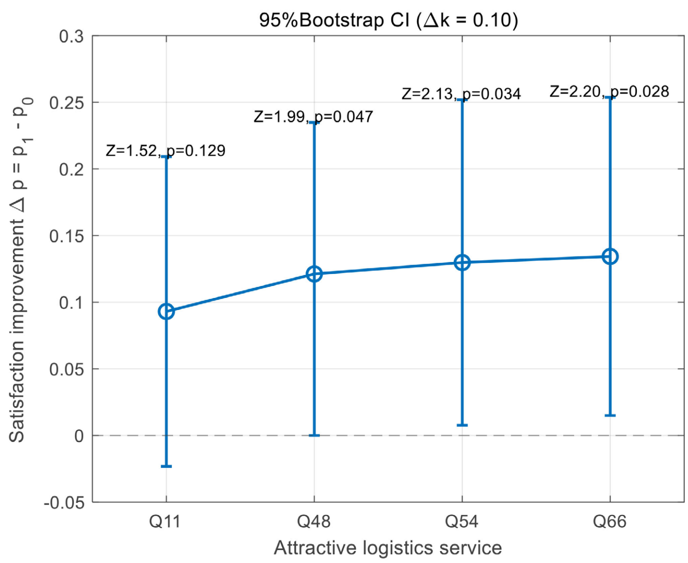

Figure 6. Bootstrap 95% confidence intervals of satisfaction proportion differences for four key attractive logistics services after TRIZ implementation when $\Delta_k = 0.10$.

Taken together, the results in Table 3 and Figures 5-7 indicate that the effectiveness of TRIZ strategies exhibits a clear stage-wise pattern: mild implementation primarily signals improvement trends, moderate implementation generates statistically significant improvements at key service nodes, and high-intensity implementation yields stable and significant satisfaction gains across all attractive services. Among these, information-driven service strategies, represented by dynamic modification mechanisms (S3) and optimized information push (S4), exhibit increased improvement elasticity, underscoring their critical role in optimizing C2B2C secondhand logistics services.

Therefore, through scenario-based estimation combined with Z-tests and bootstrap resampling based on Table 1 data, this study provides a quantitative and replicable framework for evaluating the potential effectiveness of TRIZ strategies for four key attractive logistics services, even in the absence of actual post-test survey data. It should be emphasized that the Z-test and Bootstrap analyses are conducted under hypothetical improvement scenarios rather than observed post-implementation data. The purpose is not causal inference, but to assess the potential magnitude, sensitivity, and robustness of satisfaction improvement under different levels of TRIZ implementation. Once platforms complete TRIZ implementation and collect post-test data, the same Z-test and bootstrap procedures can be directly applied, enabling a smooth transition from methodological simulation to empirical validation.

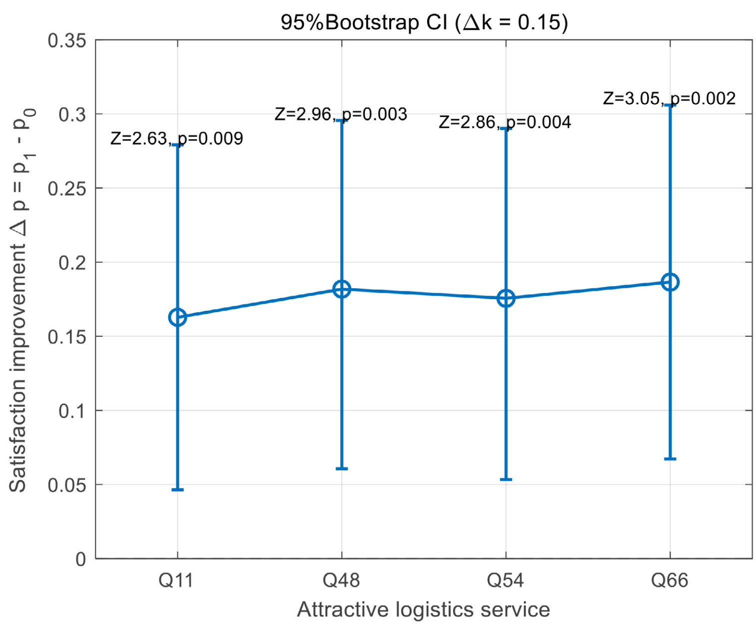

Figure 7. Bootstrap 95% confidence intervals of satisfaction proportion differences for four key attractive logistics services after TRIZ implementation when $\Delta_k = 0.15$.

5.3. Establishing an Optimized Logistics Service Operation Model for Second-Hand Platforms

Based on the preceding Kano attribute identification and TRIZ contradiction analysis, this study focuses on four attractive logistics service indicators, i.e., Q11 (timely response to pickup requests), Q48 (responsiveness of return pickup), Q54 (in-transit modification capability), and Q66 (logistics location notification), and proposes four core improvement strategies (S1 - S4). To enhance the systemic coherence of the strategy set, this study further integrates the TRIZ problem structure, the operational characteristics of C2B2C logistics, and the satisfaction improvement simulation results derived from Table 3 (Z-test and Bootstrap simulation) to construct the optimized logistics service operation model for secondhand platforms, as illustrated in Figure 8. The overall model follows a sequential implementation path of S1→S4→S3→S2, forming an integrated operational process characterized by front-end prediction, mid-process dynamism, reverse recovery, and closed-loop information feedback.

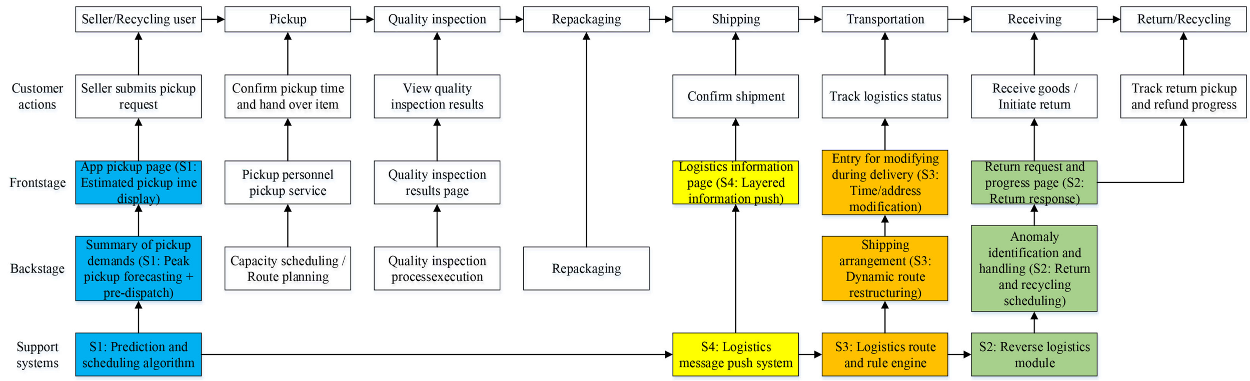

Figure 8. Blueprint for optimizing the operation of logistics services on a second-hand e-commerce platform.

1) Step 1. Implement S1: Strengthening Front-end Pickup Prediction and Dispatching Capability (Corresponding to Q11)

Pickup responsiveness marks the starting point of the C2B2C logistics chain and is a critical node that determines the stability of subsequent transportation rhythms. Simulation results in Table 3 indicate that a statistically significant improvement in satisfaction for Q11 requires an increase of approximately $\Delta_k \approx 0.15$, suggesting that users exhibit a low tolerance for pickup delays and that only substantial structural optimization can generate perceptible improvements.

Accordingly, S1 must serve as the foundation of the entire operational model. Its functions include balancing regional supply and demand through predictive modeling, preallocating pickup capacity, and reducing uncertainty in pickup waiting times. These improvements provide reliable data and operational stability for subsequent strategies, notably S3 (dynamic in-transit adjustment) and S4 (real-time information push). In other words, without front-end stability, downstream strategies cannot realize synergistic effects.

2) Step 2. Implement S4: Establishing a Unified Information Push and Service Touchpoint System (Corresponding to Q66)

Among the four indicators, Q66 shows the most remarkable improvement in sensitivity. Under the $\Delta_k = 0.10$ scenario, it is already statistically significant (p-value ≈ 0.0276) and exhibits a clearly positive bootstrap confidence interval. This result indicates that users are susceptible to information transparency and that improvements in this area can yield rapid effects without fundamentally altering the underlying operational structure.

Therefore, positioning S4 as the second step offers clear advantages: it enables rapid release of improvement outcomes and strengthens user trust; it forms a dual-factor structure with S1 combining stable supply and information transparency; it helps users develop clearer expectations regarding logistics progress, thereby increasing acceptance of subsequent dynamic modification mechanisms under S3; and it enhances overall process visibility and controllability, reducing inquiries and exception-related complaints. As such, implementing S4 at this stage represents an optimal balance among efficiency, user experience, and feasibility.

3) Step 3. Implement S3: Establishing Dynamic Route and Time Modification Mechanisms During Transportation (Corresponding to Q54)

Q54 is the earliest among the four indicators to reach statistical significance. Under the $\Delta_k = 0.10$ scenario, its p-value reaches 0.0336 (<0.05), indicating that users are susceptible to delivery flexibility. Once platforms enable controlled modification capabilities, satisfaction improves markedly.

However, effective implementation of S3 requires two prerequisites: front-end stability, ensured by S1 to prevent systemic disruption from dynamic adjustments, and transparent information delivery, provided by S4, to ensure users receive timely confirmations and routing feedback. Therefore, S3 is best positioned after S1 and S4, allowing dynamic capabilities to act as an "experience amplifier" within the overall model, enabling users to perceive process flexibility and platform professionalism.

4) Step 4. Implement S2: Building an Efficient Door-to-door Return Pickup System (Corresponding to Q48)

Statistical results for Q48 reveal a "lagged improvement" pattern: satisfaction does not reach statistical significance at $\Delta_k = 0.10$ but improves markedly at $\Delta_k = 0.15$. This pattern reflects the inherent complexity of reverse logistics, which involves coordination among platform-owned teams, partner couriers, and third-party networks. Improvements must be built upon stable forward logistics (S1), effective information dissemination (S4), and dynamic adjustment capabilities (S3). Isolated optimizations rarely yield immediate improvements to experience; instead, system-level upgrades are required.

Consequently, placing S2 after S3 is logically sound because reverse logistics optimization represents the "final value realization point" of the service system. When implemented after overall system stabilization, its improvement effects become more salient and sustainable.

5) Integrated Operational Model: S1→S4→S3→S2

By integrating the four strategies, a logistics service operation model aligned with C2B2C characteristics, user perception logic, and TRIZ contradiction resolution principles emerges (**Figure 8**):

a) S1 (Front-end prediction): Stabilizes the process entry point and reduces time loss and uncertainty;

b) S4 (Real-time information push): Enhances perceived transparency and reduces information gaps;

c) S3 (Dynamic modification): Improves system adaptability and routing/time flexibility;

d) S2 (Reverse recovery): Enhances end-to-end efficiency and reduces service delays and responsibility ambiguity.

These four strategies progress sequentially and reinforce one another, ultimately forming a high-resilience, high-transparency, and high-efficiency logistics service model for secondhand platforms, characterized by front-end prediction (S1), mid-process dynamic adjustment (S3), end-stage reverse recovery (S2), and full-process information closure (S4).

6. Conclusion

This study investigates logistics service optimization in C2B2C secondhand e-commerce platforms by focusing on the heterogeneity and complexity of user demand structures embedded in multistage, closed-loop logistics processes. The primary objective is to identify the critical logistics service elements shaping the user experience and to develop an actionable framework to improve logistics services. By integrating user-generated review corpus analysis, Kano model-based demand attribute identification, and the TRIZ methodology, this study establishes a systematic analytical framework encompassing four stages: demand identification, mechanism analysis, strategy formulation, and effectiveness evaluation.

The results indicate that in the C2B2C secondhand transaction context, users' concerns regarding logistics services extend well beyond traditional delivery timeliness. Instead, user attention is spread across several key service nodes, including pickup responsiveness, return-collection efficiency, process flexibility, and information transparency. On the basis of the Kano model and Better-Worse coefficient analysis, four attractive logistics service attributes with significant positive effects on user satisfaction are identified: timely response to pickup requests, prompt door-to-door return collection, flexibility in modifying delivery time and address during transit, and transparent logistics information notifications. While the absence of these services does not necessarily lead to strong dissatisfaction, their adequate provision can remarkably enhance overall satisfaction, reflecting the nonlinear nature of user demand.

Building on these findings, the study applies the TRIZ methodology to analyze the underlying mechanisms of the identified key demands by mapping them onto systemic contradictions within logistics operations. Four core optimization strategies are subsequently derived: a proactive dispatching and demand forecasting mechanism, a standardized and efficient return collection system, a dynamic in-transit route and time modification mechanism, and a tiered information notification scheme. Compared with traditional experience-based or single-point improvement approaches, this integrated strategy set addresses the core challenges of C2B2C logistics systems, namely, high uncertainty, multiple service nodes, and information asymmetry, through coordinated improvements in process structure, information flow, and decision-making mechanisms.

To assess the potential effectiveness of the proposed strategies, the study constructs plausible scenarios for improved satisfaction based on pretest survey data. It employs two-proportion Z-tests and bootstrap resampling for quantitative estimation. The simulation results show that delivery modification flexibility and logistics information notifications achieve statistically significant or near-significant improvements in satisfaction, return collection efficiency exhibits marginally substantial gains, and pickup responsiveness demonstrates notable potential for improvement. These findings suggest that the proposed TRIZ-based strategies can generate positive effects across multiple logistics service nodes, with impact magnitudes closely related to service characteristics and process complexity.

Overall, this study contributes theoretically by extending the integrated application of the Kano model and TRIZ methodology to platform-based logistics service research. Methodologically, it proposes an evaluative approach to estimating the effectiveness of strategies when postintervention data are unavailable. In practice, it offers a systematic and replicable decision-making reference for C2B2C secondhand e-commerce platforms seeking to optimize logistics operations, enhance user experience, and achieve competitive differentiation. Future research may further validate and refine the proposed framework through empirical testing once real postimplementation data become available, enabling dynamic optimization of the model and conclusions.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

Akerlof, G. A. (1970). The Market for “Lemons”: Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics, 84,* 488-500.
https://doi.org/10.2307/1879431

Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the Pricing Power of Product Features by Mining Consumer Reviews. *Management Science, 57,* 1485-1509.
https://doi.org/10.1287/mnsc.1110.1370

Bitner, M. J., Brown, S. W., & Meuter, M. L. (2000). Technology Infusion in Service Encounters. *Journal of the Academy of Marketing Science, 28,* 138-149.
https://doi.org/10.1177/0092070300281013

Carbone, V., Rouquet, A., & Roussat, C. (2017). The Rise of Crowd Logistics: A New Way to Cocreate Logistics Value. *Journal of Business Logistics, 38,* 238-252.
https://doi.org/10.1111/jbl.12164

Chen, S. Q. (2024). Research on a Community-Based Comprehensive Second-Hand Goods Trading Platform Based on the Ethereum Technology and C2B2C Mode. *Office Automation, 29,* 87-90.

Chen, T., & He, Y. P. (2008). Differences between the Importance and Satisfactory Measures of Logistics Center Service. *Maritime Quarterly, 17,* 23-48.

Cui, Z., Yang, C., Wang, J., & Qin, Y. T. (2025). LDA Theme and KANO Model under the Micro-Short Play User Demand Survey—An Empirical Study Based on 585 Questionnaires. In *Proceedings of the 2025 Annual Conference of the Chinese Society of Business Statistics* (443-470). Commerce Statistical Society of China.

Dai, Y., Wang, Y., Xu, B., Wu, Y., & Xian, J. (2020). Research on Image of Enterprise After-Sales Service Based on Text Sentiment Analysis. *International Journal of Computational Science and Engineering, 22,* 346-354. https://doi.org/10.1504/ijcse.2020.107367

Esfahanian, S., & Lee, E. (2022). A Novel Packaging Evaluation Method Using Sentiment Analysis of Customer Reviews. *Packaging Technology and Science, 35,* 903-911. https://doi.org/10.1002/pts.2686

Fan, J. (2021). The Future of Circular Economy: Second-Hand E-Commerce. *Scientific Journal of Economics and Management Research, 3,* 44-49.

Fernando, A. G., Sivakumaran, B., & Suganthi, L. (2018). Comparison of Perceived Acquisition Value Sought by Online Second-Hand and New Goods Shoppers. *European Journal of Marketing, 52,* 1412-1438. https://doi.org/10.1108/ejm-01-2017-0048

Gao, Y. X., & Sun, B. Z. (2024). Research on Fusion Media Network Information Push Based on the Perspective of Network Behavior Tracking of "Post-00s" College Students. *Operations Research and Management Science, 33,* 211-217.

Geissdoerfer, M., Savaget, P., Bocken, N. M. P., & Hultink, E. J. (2017). The Circular Economy—A New Sustainability Paradigm? *Journal of Cleaner Production, 143,* 757-768. https://doi.org/10.1016/j.jclepro.2016.12.048

He, Y. Y., & Lv, Y. W. (2012). The Practical Research on the Influencing Factors of Logistic Service Quality and Customer Loyalty. *China Business and Market, 26,* 79-82.

Holloway, B. B., & Beatty, S. E. (2003). Service Failure in Online Retailing: A Recovery Opportunity. *Journal of Service Research, 6,* 92-105. https://doi.org/10.1177/1094670503254288

Hou, J., Liu, W., Cao, Y., Wang, S., & Tang, O. (2024). Evaluating Service Quality of Express Logistics Service Based on Online Reviews Using LDA-LSTM. *Journal of Management Science and Engineering, 9,* 308-327. https://doi.org/10.1016/j.jmse.2024.02.001

Hu, K. C., Chia, K. C., Lu, M., & Liang, Y. L. (2022). Using Importance-Performance Analysis, Goal Difficulty and the Kano Model to Prioritize Improvements in the Quality of Home Delivery Logistics Services. *The International Journal of Logistics Management, 33,* 477-498. https://doi.org/10.1108/ijlm-12-2020-0491

Jin, W. W. (2022). Research on Reverse Logistics Optimization of C2C e-Commerce Third-Party Returns. *Logistics Technology, 45,* 76-78+82.

Jing, Y. (2025). Research Progress on the Efficient Utilization of Biochar under the Background of "Dual Carbon" Goals. *Recyclable Resources and Circular Economy, 18,* 47-50.

Kano, N., Seraku, N., Takahashi, F., & Tsuji, S. (1984). Attractive Quality and Must-Be Quality. *Journal of The Japanese Society for Quality Control, 14,* 147-156.

Li, W. C., Liu, S. Q., & Guo, R. L. (2025). Research on AI Search User Expectations Based on the Kano Model. *Information Studies: Theory & Application, 48,* 122-130.

Liu, S., Weng, L., Qin, J., & Sun, S. (2025). User Needs Analysis of University Library APP Based on Kano Model. In *Proceedings of the 2025 International Conference on Artificial Intelligence and Product Design* (pp. 242-247). ACM. https://doi.org/10.1145/3765416.3765456

Lu, J. W., Yuan, Y. F., & Chen, Y. (2025). User Demand Analysis and Optimization Strategies for Scientific Data Sharing Platforms under Kano Model. *Library Work and Study, 1,* 45-56.

Matzler, K., & Hinterhuber, H. H. (1998). How to Make Product Development Projects More Successful by Integrating Kano's Model of Customer Satisfaction into Quality Function Deployment. *Technovation, 18,* 25-38. https://doi.org/10.1016/s0166-4972(97)00072-2

Mikulić, J., & Prebežac, D. (2011). A Critical Review of Techniques for Classifying Quality Attributes in the Kano Model. *Managing Service Quality: An International Journal, 21,* 46-66. https://doi.org/10.1108/09604521111100243

Mittal, V., Ross, W. T., & Baldasare, P. M. (1998). The Asymmetric Impact of Negative and Positive Attribute-Level Performance on Overall Satisfaction and Repurchase Intentions. *Journal of Marketing, 62,* 33-47. https://doi.org/10.1177/002224299806200104

Olsson, J., Hellström, D., & Vakulenko, Y. (2023). Customer Experience Dimensions in Last-Mile Delivery: An Empirical Study on Unattended Home Delivery. *International Journal of Physical Distribution & Logistics Management, 53,* 184-205. https://doi.org/10.1108/ijpdlm-12-2021-0517

Pan, Y. (2025). Research on the Commodity Alienation of Second-Hand e-Commerce Platforms from the Perspective of Circular Economy. *e-Commerce Letters, 14,* 429-435. https://doi.org/10.12677/ecl.2025.1482537

Pandey, S., Mittal, S., & Chawla, D. (2024). Tackling Consumer Information Asymmetry and Perceived Uncertainty for Luxury Re-Commerce through Seller Signals. *Journal of Retailing and Consumer Services, 79,* Article ID: 103736. https://doi.org/10.1016/j.jretconser.2024.103736

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). SERVQUAL: A Multiple-Item Scale for Measuring Consumer Perceptions of Service Quality. *Journal of Retailing, 64,* 12-40.

Patrício, L., Fisk, R. P., & Falcão e Cunha, J. (2008). Designing Multi-Interface Service Experiences: The Service Experience Blueprint. *Journal of Service Research, 10,* 318-334. https://doi.org/10.1177/1094670508314264

Pavlou, P. A., & Gefen, D. (2004). Building Effective Online Marketplaces with Institution-Based Trust. *Information Systems Research, 15,* 37-59. https://doi.org/10.1287/isre.1040.0015

Rao, S., Goldsby, T. J., Griffis, S. E., & Iyengar, D. (2011). Electronic Logistics Service Quality (e-LSQ): Its Impact on the Customer's Purchase Satisfaction and Retention. *Journal of Business Logistics, 32,* 167-179. https://doi.org/10.1111/j.2158-1592.2011.01014.x

Rashid, D. A., & Rasheed, D. R. (2024). Logistics Service Quality and Product Satisfaction in e-Commerce. *Sage Open, 14,* 1-12. https://doi.org/10.1177/21582440231224250

Ravula, P. (2020). Impact of Delivery Performance on Online Review Ratings: The Role of Temporal Distance of Ratings. *Journal of Marketing Analytics, 11,* 149-159. https://doi.org/10.1057/s41270-022-00168-5

Sun, J., Li, X., Wang, Z., & Chen, Z. (2025). Robust Optimization of Uncertain e-Commerce Closed-Loop Supply Chain Networks under Carbon Policies. *Scientific Reports, 15,* Article No. 34308. https://doi.org/10.1038/s41598-025-21519-z

Tirunillai, S., & Tellis, G. J. (2014). Mining Marketing Meaning from Online Chatter: Strategic Brand Analysis of Big Data Using Latent Dirichlet Allocation. *Journal of Marketing Research, 51,* 463-479. https://doi.org/10.1509/jmr.12.0106

Vakulenko, Y., Hellström, D., & Hjort, K. (2019). What's in the Parcel? Exploring Customer Value in e-Commerce Last-Mile Delivery. *Journal of Business Research, 99,* 362-373.

Wachinger, J., Reñosa, M. D. C., Guevarra, J. R., Landicho-Guevarra, J., Demonteverde, M. P., Silvestre, C. et al. (2023). Keeping the Customer Satisfied: Applying a Kano Model to Improve Vaccine Promotion in the Philippines. *Global Health: Science and Practice, 11,* e2300199. https://doi.org/10.9745/ghsp-d-23-00199

Wang, C. Y., Wen, H. M., Guo, S. N., Lin, Y. F., & Wan, H. Y. (2023a). Multi-Task Deep Spatial-Temporal Network for Couriers' Pick-Up Arrival Time Prediction. *Computer Engineering & Science, 45,* 136-144.

Wang, Y., Zamudio, C., & Jewell, R. D. (2023b). The More They Know: Using Transparent Online Communication to Combat Fake Online Reviews. *Business Horizons, 66,* 753-764. https://doi.org/10.1016/j.bushor.2023.03.004

Xiong, H. X., Zhan, X. M., & Zheng, X. W. (2024). Research on Optimization of Health Website Information Service Quality Based on KANO-QFD Integration Method. *Information Studies: Theory & Application, 47,* 160-170+179.

Yang, Y., & Yuan, Y. (2022). Research on the Correlation between the Quality of Logistics Service and the Volume of Express Delivery in China. *Management Science and Engineering, 11,* 83-96. https://doi.org/10.12677/mse.2022.111011

Zhang, M., Zhang, L., Zhi, X., Cheng, F., Yao, Y., Deng, R. et al. (2024). Demand Analysis of Health Care Services for Community-Dwelling Breast Cancer Survivors Based on the Kano Model: A Cross-Sectional Study. *International Journal of Nursing Sciences, 11,* 171-178. https://doi.org/10.1016/j.ijnss.2024.03.015

Zhang, X. Y., & Wang, F. (2024). Function Optimization of Government Intelligent Q&A System Based on KANO Model. *Information Science, 42,* 54-64.

Zhang, Y. (2025). Research on Business Model Innovation of Second-Hand Book e-Commerce Platform—A Case Study of "Duozhuayu". *E-Commerce Letters, 14,* 3097-3102. https://doi.org/10.12677/ecl.2025.141388

Zhao, W. X. (2020). *Research on the Optimization of Logistics Network of Internet Secondhand Trading Platform in C2B2C Mode*. Master Thesis, China University of Geo-sciences.

Zhao, Y. Q., Ruan, P. N., Liu, X. Y., & Shan, X. H. (2020). Study on User Satisfaction Evaluation Based on Online Comment. *Management Review, 32,* 179-189.

Zhu, Z., Wen, Z. C., & Zang, J. (2024). Research on Optimization of e-Commerce Express Terminal Distribution Mode. *Journal of Wuhan University of Technology (Information & Management Engineering), 46,* 139-145+153.