



CERTIFICATE OF RESEARCH IN BUSINESS ADMINISTRATION

**Behavior-Driven Reverse Supply Chain Design in Live-
Streaming Commerce: An Integrated Behavioral–Operational
Framework**

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Chapter 1 - Area of research, relevance, and contribution to the area

The fast expansion of Live Streaming Commerce(LSC) — on platforms such as TikTok Shop, Taobao Live, Youtube Live and Facebook Live — has created a new and highly interactive digital marketplace with surging growth in terms of market size and user penetration(Statista, 2025). The main mechanism in live-streaming commerce is different from traditional E-commerce that introduces and promotes the product through the one-way image, text or video description, resulting in low interaction between merchants and consumers. While LSC uses video content on digital platforms to sell products and services in real time through two-way and interactive communication. To facilitate the transaction process LSC involves three important elements: influencer/celebrity, consumer engagement, and technology factors (Purboyo, 2025). Among those factors influencer or celebrity plays a pivotal role in establishing trust and credibility for the products being promoted. In LSC transaction consumer's impulse buying and influencer-induced overselling often lead to surging return rate even much higher 10%-20% than traditional on line retailing platform(Xiao, 2025). The high return rate poses major challenges for reverse supply chain operation to handle volume volatility and improve customer satisfaction(Tan, 2023). The reverse supply chain cost affected by the high return rate will be a significant contributor to the financial success in LSC operation.

Most existing researches in LSC and the related product return focus on examining consumer behavior linking with LSC mechanism and few studies on the linkage with reverse supply chain(RSC) operation efficiency(Priya, 2022). Meanwhile traditional RSC models focus on logistics network design as well as internal operation process optimization failing to capture behavioral spikes that is typical of LSC high return contribution (Marta, 2023). In LSC operation the RSC should be designed by the characteristics of LSC mechanism to achieve more efficiency and cost affordability for operation. So this research will penetrate into consumer behavioral drivers in LSC and how they affect return flow uncertainty, establish the relationship between those drivers and RSC design elements, finally propose an integrated framework linking behavioral determinants of return intention with RSC operation variables.

Unlike traditional research that treats product return as exogenous or defect driven, this research demonstrates that a significant portion of returns in live streaming commerce is behavioral driven and therefore predictable, manageable and designable. The behavioral-operational model potentially contributes the management team to optimize operation and financial efficiency in LSC return management, specifically through improving return forecast

accuracy with consideration of behavioral signals, integrating cross function (commercial and operational) planning process to design right size capacity and developing real time digital solution to translate behavior indicators into effective and efficient reverse logistics design elements.

Chapter 2 - Research question being addressed

The high return rate in living streaming commerce is driven by many factors that are different from traditional e-commerce because of the immediate, interactive and immersive transaction nature of live streaming. From the literature review those factors could be categorized into five groups -

- 1) Consumer Psychological & Behavioral drivers are the most critical factors for return that includes impulse buying, expectation-reality gap, Influencer/Celebrity effect and low product knowledge before purchase.
- 2) Streamer & Content credibility relates to influencer/Anker's effect by the communicated contents on over promotion, mis-leading claims, product information accuracy.
- 3) Product category characteristics relate to different product category for different return rate in terms of size/variation complexity and user habits.
- 4) Platform & policy-related factors include return policy flexibility, transaction speed and poor after sale customer service.
- 5) Supply chain & logistics design factors includes poor last mile delivery quality and product quality inconsistency.

So the research needs to answer the first question which are key drivers to influence product return and will focus on the most critical factors - consumer behaviors.

The natural mechanism of high return intention in LSC leads to unpredictable return volume variability and uncertainty. That has significant impact on reverse logistics handling cost, capacity requirements, lead time/processing time, recovery value of returned products, etc. So the following questions should answer what is the linkage between return intentions and reverse supply chain performance .

To build the integrated behavioral – operational model, the below three key questions will be studied -

1) What are key behavioral drivers to influence return intention in live streaming commerce?

This is the main research area for LSC in recent years. Flow theory (Hoffman & Novak, 2009) is applied to study impulsive buying behavior in LSC; Expectation-Confirmation Theory is used to study the return intent caused by the expectation gap when consumers see and feel the product. Meanwhile the other key elements in LSC are also studied widely i.e. influencer/streamer's credibility, Return policy leniency, etc.

2) How does return intention affect return volume, variability and processing leadtime?

The return intention leads to return rate uncertainty, and the related return volume and variability which affect the reverse supply chain performance. The return intention doesn't cause 100% return action but there is the probability from return intention to return action. This research question is studied to clarify the return intention impact on the inputs for reverse supply chain.

3) What is integrated behavioral – operational model to optimize both consumer experience and reverse supply chain performance to tackle the high return challenge?

Considering the behavioral elements and the related return intention, the integrated behavioral – operational model is set up to optimize the reverse supply chain performance. The final research question will be studied and clarified to further understand the behavior impact on operation performance.

Chapter 3 - Literature review

The rapid growth of live streaming commerce(LSC) has introduced a new set of e-commerce dynamics that amplify consumers' impulsive purchasing and emotional decision making strengthened by streamer/anchors' social influence during on line shopping. These behaviors translate directly into elevated return intention and volatile return flow, which finally impose significant pressures on reverse supply chain (RSC) systems. LSC and RSC have been both widely studied but few models integrate behavioral drivers with return flows and reverse supply chain optimization. So this chapter reviews existing researches across below five domains to build the framework from behavioral drivers to return intention and from return intention to reverse supply chain operation.

- 1) Live streaming commerce and consumer behaviors
- 2) Return intention in LSC
- 3) E-commerce returns and reverse supply chain
- 4) Reverse supply chain design and performance
- 5) Integrated behavioral-operation research

3.1 Live Streaming Commerce and consumer behaviors

Live stream commerce(LSC) emerges from electronic commerce (E-commerce) since 2017 and currently beocmes the dominant retail channel in China, Southeast Asia, and fast growing in Western markets. The livestream market in China has grown 57 times bigger from 2019 to 2023 and continues to expand (Shou, 2023) and other big live commerce markets such as the United States (40%), Germany (26%), and Japan (15%) are far behind (Hong, 2023). As a dynamic format of e-commerce LSC enriches the shopping experience with real-time transmission such as live audio-visual broadcasting and frequent interaction, offering consumers engaging and entertainment atmosphere to discover and purchase products and service(Luo, 2025). Moreover, the performance of online celebrities(streamer/celebrity) can stimulate consumers' emotions and thus enhance consumers' purchase intention regarding the products recommended. Finally the interaction generates significant online traffic and sales for business. Generally the live streaming commerce has below features -

- 1) Authenticity: live streaming shows the real product and using process through real time broadcast and interaction between streamers and consumers, which can better present accurate and real information to consumers than traditional e-commerce text, image and video.
- 2) Real-time interactivity: the communication network (live broadcast rooms) builds real time interaction between operators/streamers and consumers. Moreover, information technology optimizes interactive behaviors through toolkits for consumer engagement and significantly improves transaction efficiency.
- 3) Immersion atmosphere: the live broadcast room connects multiple consumers at the same time and in the same place with the same interests for streamer and product, forming immersion atmosphere of everyone participating and stimulating the participator's impulse buying intent.

All the above LSC characteristics affects consumer behaviors in transaction and further lead to diversified purchasing intention. Purchase intention refers to the combination of consumers' interest in a brand or a product and the possibility of purchasing these items (Gupta, 2021) that is a crucial factor to affect business success or failure. In LSC there are various factors related to consumer purchasing intention since multiple stakeholders are involved in the transaction process such as streamer, consumer, product and platform (Fei, 2025). The summarized key factors from literature review are listed below -

- 1) Streamer's credibility - The credibility can be divided into three characters – attractiveness, trustworthiness and expertise. Attractiveness refers to streamers' endorsement to attract more consumers' attention and participation. Trustworthiness is built from the streamer's dignity, believability, and honesty that significantly impacts both cognitive and affective states in the context of live streaming commerce. Expertise is the proficiency level of product knowledge endorsed by the streamer and usage that decides consumer's convincing for the decision making to purchase (Xu, 2022)
- 2) Product evaluation – the LSC demonstrates the authentic information to consumers as well as positive peer feedback, interactive discussion and real time live broadcast in manufacture and logistics flows (Bourreau and Gaudin, 2022). The consumer will make purchasing decisions from various aspects of feeling and judgement.
- 3) Platform design - The related policy designed by the platform will significantly affect consumer's purchasing intent such as transaction easy for use, logistics efficiency, after sale service and return policy leniency (Kim, 2023).
- 4) Price promotion and perceived value - A promotional incentive is a coupon, rebate, discount, cash back or other promotional device offered to induce a consumer to purchase goods or services at a lower price. Specifically, in LSC flash sale is frequently used by the merchant for a short period of time only. The stress from time limitation can inspire consumers to make impulse purchases because they are afraid of losing the opportunity to buy at a lower price (Gu, 2023).
- 5) Live interactivity – LSC creates two type of interactivity - 1) Streamer and consumer - High-frequency consumer–streamer interactions make consumers willing to engage in discussion and participation in the shared chat rooms, which decreases consumers' perceived risk of the products and inspires impulsive buying behavior. 2) Consumer and consumer - Different consumers in the live broadcast room can see comments on the screen and share their

comments and chat with each other that enhances other consumers' perceived persuasiveness and thus increases purchase intention (Gu, 2023).

3.2 Return intention in LSC

The consumers in LSC have strong impulse purchasing intent through the interaction with streamer/anchors. Meanwhile, that also leads to very high return intention after purchasing. The return rate even reaches 60% to 70% (Tan, 2023) differing from product categories. The literature review below lists down the key theories to study high return intention in LSC -

- 1) Flow theory and impulsive buying – Flow theory has been adapted to web related ecommerce to explain how and why users become absorbed in online environments. This research concludes compelling online flow experiences created by congruence of skill and challenge, interactivity, vividness, and motivation lead to increased learning, perceived behavioral control, exploratory mindset, and positive subjective experience (Hoffman & Novak, 2009). Flow state experienced by consumers increases customer satisfaction and loyalty and further increases impulse purchases. The enjoyment from the flow state is encountered during shopping but true satisfaction may only be achieved later when they believe they have made a wise choice. This scenario can result in the emergence of negative emotions, including regret and unmet expectation leading to higher product returns (Kumar, 2024).
- 2) Expectation–Reality Gap (ERG) - Expectation–Disconfirmation Theory (EDT) developed by Richard L. Oliver in the late 1970s-1980s explains that consumer satisfaction and downstream outcomes depend on the difference between pre-purchase expectations and perceived performance after experience (Oliver, 1977/1980). When actual performance exceeds expectation, there is positive disconfirmation and increased satisfaction; when performance falls short, negative disconfirmation leads to dissatisfaction and potentially adverse behaviors (Bhattacharjee, 2001). Following EDT application in e-commerce Expectation–Reality Gap (ERG) is developed to explain the high return rate for consumer to feel the reality gap vs the expectation during shopping (Sergio, 2023). In addition to immediate satisfaction or discontinuance outcomes, ERG frameworks are relevant to broader behavioral phenomena in live streaming - the better presentation of the product in live camera, the exaggeration of product features by the streamer and the impulsive buying intent in limited time constraint (Feng, 2024). When expectation perceptions are positively shaped (i.e., consumers perceive that what they expect aligns with what they experience), they are more likely to buy impulsively. Conversely, mismatches can reduce this effect. Similarly,

research on performance expectations within live streaming shopping indicates that accurately managing expectations about product functionality and demonstration reliability helps improve satisfaction and subsequent purchase intention. This again reflects the broader disconfirmation paradigm: aligning or exceeding expected performance tends to boost favorable attitudes and repeated engagement.

- 3) Influencer/Streamers' credibility – Streamer's credibility, trustworthiness and expertise reduce perceived risk, increase confidence and lower return intention (Kim, 2023). On contrast the lower credibility and overpromotion will results in higher mismatching expectation after unboxing the product and higher likelihood of product return.
- 4) Return policy leniency - High lenient return policy is set to enhance customer satisfaction (Heim and Field, 2007) to worry about after-sale service as an overall evaluation of products and services to mitigate the purchase risk (Woimant, 2025). Satisfied customers are more likely to make further purchases as well as to tell others about their experiences via word-of-mouth. Meanwhile high lenient return policy leads to high return rate considering the return cost and service efficiency and the design elements for return policy have different impact on return rate (Quang, 2025).

All the dynamics in LSC are intensified vs traditional E-commerce because of the impulsive and low-deliberation nature of purchase. The study of which consumer behavior decides return intention will be critical for further operation model setup.

3.3 E-commerce returns and reverse supply chain

The retail industry has been transformed dramatically in recent decades due to the internet enabling online shopping, accelerated by electronic information technology and large E-commerce platform uprising. In recent years E-commerce has been further strengthened with social media and live streaming emergence enabled by smart mobile continuous penetration. As global internet access and adoption rapidly increase the number of people making purchases online is ever-increasing to over five billion internet users worldwide. In 2025, retail e-commerce sales are estimated to exceed 4.3 trillion U.S. dollars worldwide, and this figure is expected to reach new heights in the coming years. (Statista, 2025).

The rapid growth in E-commerce creates a fantastic revenue generating opportunity for on- line retailers, but it also carries challenges associated with expanded operations to handle both order fulfillment and customer returns (Robertson, 2020). As assessed 30% of all products ordered

online get returned, compared with 9% bought in brick-and-mortar stores. Average return rates vary by category, but clothing and shoes bought online typically have the highest rates with 30 to 40 percent returned (Reagan, 2019). In Europe around seven percent of the overall E-commerce market revenue was returned in 2024, with more than half of shoppers sending back products purchased online in some European countries(Statista, 2025). Specifically LCS in social media platform even intensifies the return rate to 50% -60% due to psychological and contextual drivers (Tan, 2023).

The high return rate in LCS turns into high return variability for reverse supply chain (Dhirendra, 2022). The return volume and sequence are highly unpredictable and volatile since consumers possibly have return intents and actions in the whole live streaming commerce transaction process affected by various random factors such as streamers counseling sell, flash sale time pressure, discrepancy from real product presentation, peer reviewer' comments after getting the product etc. The high uncertainty has significant impact not only on reverse supply chain capacity, inventory allocation, inspection/handling/refurbishment/disposal cost, and staff arrangements but also customer satisfaction for brand loyalty and product repurchasing intent (Anthony and Julia, 2024).

3.4 Reverse supply chain design and performance

Reverse supply chain (RSC, also called reverse logistics) is the return process to move back the products from consumer to manufacturer, and a lot of physical activities need to be implemented for product inspection, refurbishment, recycling, and disposal (Govindan, 2017). Considering high return rate in E-commerce the reverse supply chain is increasingly important to manage cost and efficiency risk in return process. Meanwhile to meet government stricter regulation and more circular economy requirement there are many studies on circular RSC loop design to avoid cost and waste of the returned products (Marta and Lougi, 2023).

A typical reverse supply chain will have typical components and processes as shown in Figure 1. The consumer initiates the return, and the product will go through collection and transportation till the returning warehouse receives it. And the internal return process will be triggered to inspect and sort the product with restocking, refurbishing, remanufacturing, recycling and scrapping (Prajapati 2019).

To design and operate the effective and efficient reverse supply chain, below elements and variables should be carefully considered –

- 1) Network configuration and facility placement - determine whether centralized or decentralized location is chosen for fast turnaround and low transport cost.
- 2) Capacity planning and layout – support varied processing of variable return flow with sufficient capacity and flexibility. Specifically, the large return volume after LSC promotion will be key challenge.
- 3) Triage and disposition rules - decide how to design standards and rules to balance the efficiency of return handling and customer satisfaction and return handling cost.
- 4) Information flow and IT integration - synchronize the return information (product, volume, timing, location, etc.) among all the stakeholders in return process i.e. consumers, streamers, platform, customer service, logistic operation, quality assurance and brand operation.
- 5) Inhouse or outsourcing - which supply network is designed to balance cost, handling capacity and quality risk.

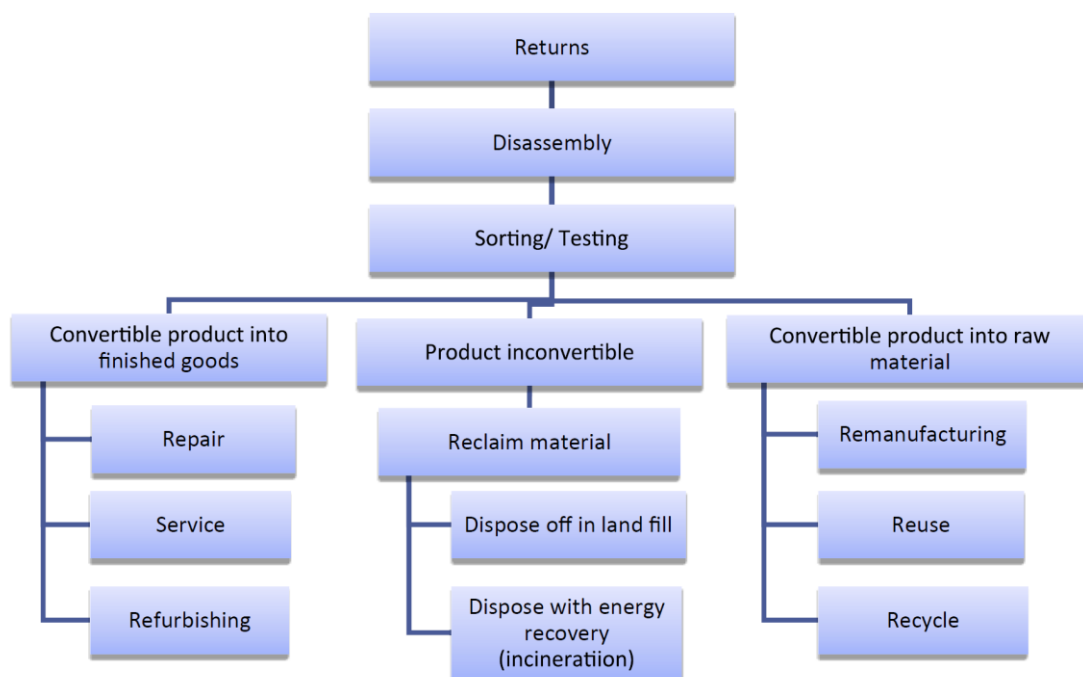


Figure 1. A generalized Reverse Logistics Structure from Prajapati 2019

The uncertainty for RSC comes from the return volume, return timing, product condition, recovery value, policy change and supply disruption(Guide, 2009). The performance of RSC is normally measured by Return rate, Processing leadtime, Cost per unit and Disposal cost to support business success and improve customer satisfaction(Salvatore, 2016).

3.5 Integrated behavioral-operational research

Currently most researches on return behavior-operation are focusing on how consumer behavior affects the sale demand not the return flow (Karl, 2024). Contraformer (Contrastive transformer) method is studied to predict product returns in live streaming e-commerce by leveraging fine-grained streamer behavior features extracted from three modalities i.e., visual, acoustic, and language (Zhang, 2025). However, there is no standard framework linking behavioral constructs to RSC operational variables due to lack of transformation methodology from psychological inputs to operational quantitative outputs. So this research will try to establish a complete and transparent framework to bridge LSC behavior drivers and RSC operation variables.

Chapter 4 - Research model or the analytical framework

4.1 Research model

Consumer behavioral will significantly impact return intention. Meanwhile return intention leads to return volume uncertainty to impact reverse supply chain design and operation. To build the integrated behavioral-operational framework the conceptual research model is showed in Figure 2. This model integrates consumer behavioral antecedents with downstream reverse supply chain operations and performance.



Figure 2. Conceptual research model for consumer behavioral - operation framework

4.2 Independent ,Dependent and Moderate Variables

The research model shows consumer behaviors lead to return intention and further impacts reverse supply chain design and operation. So consumer behavioral drivers are independent variables and reverse supply chain operation performance are dependent variables. Return intention is mediator to link consumer behavioral and reverse supply chain operation.

Independent variables

Since the research is focusing on the study from behavior element to return intent so the main consumer behavioral drivers for return will be defined as independent variables as below -

- 1) impulsive buying tendency (IBT) - stimulated by urgency, limited time discount or interactive pressure in live streaming
- 2) expectation-reality gap (ERG) - consumer's feeling of the discrepancy from the initial expectation in live streaming and the real judgement after receiving the product
- 3) streamer/anchor credibility (SC) - the trust build from the streamer and consumer by experience and reputation.
- 4) product presentation quality (PPQ) - the clarity and realism from live streaming's visual demonstration
- 5) perceived risk (PR) - the perceived potential quality, financial and mismatch risk when consumer buy the product or service in LSC

Dependent variables

The high return intention in LSC will cause the high return variability and uncertainty. To handle those challenges the reverse supply chain design need to consider key elements on capacity, cost and processing time efficiency.

- 1) return variability and uncertainty (RVU) - volatility of the return
- 2) return volume (RV)- expected product numbers of return
- 3) return processing timing (RPT)- the logistics network and internal processing time to finish the return supply chain operation
- 4) reverse logistics cost (RLC) - the cost of handle, inspect, restock and disposal/refurnish the returned product
- 5) recovery efficiency (RE) - the whole product return management efficiency to achieve consumer satisfactory enabled by sufficient staffing, inspection queue, warehouse space and other required capacity

Mediate variables

Return intention (RI) is the main behavioral mechanism linking consumer psychology to reverse supply chain operational performance. That is output of consumer behavioral and input for reverse supply chain design.

Moderate variables

There are many moderate variables affecting the behavior elements to return intent and further to operation performance ie return policy leniency, consumer experience, product categories, etc . However, given the study's focus on identifying the core behavioral mechanism linking live streaming commerce to reverse supply chain design, this research prioritizes parsimony and moderating effects are intentionally deferred for future research.

4.3 Research Hypothesis

This behavioral-operational research model has two phase study - Behavioral drivers cause return intention and return intention affects reverse supply chain performance. To make the study more relevant to RSC design element optimization, the hypothesis will be selected more relevant to which potentially help behavioral and operational improvement in practice. So considering all independent, dependent , moderate and mediate variance analysis the research will set up below hypothesis –

Different behaviroal drivers in LSC ie impulsive buying behavior, expectaion- reality gap etc will have the effect on consumers' return intent according to the previous studies. So the first hypothesis is

H1: Behavioral factors in LSC positively influence consumers' return intention.

To study the detailed factors below hypothesis will be studied and tested

H1a: Impulsive buying behavior positively influences return intention

H1b: Expectation-Reality Gap positively influences return intention

H1c: Streamer Credibility negatively influences return intention.

H1d: Product presentation quality negatively influences return intention.

H1e: Perceived risk positively influences return intention

Higher return intention translates into higher return volume and increased uncertainty in return timing and quantity. Behavioral-driven returns tend to be clustered temporally and less predictable than defect-driven returns. Such variability increases operational complexity in the whole return management process. So the second hypothesis is

H2: Return intention positively affects reverse supply chain return volume, variability and time concentration.

High return volume and variability requires more manufacturing capacity to receive, inspect, sort, restock, repack and dispose the returned products. All the operation complexity increase will lead to high operation cost and low recovery efficiency. So the study needs to clarify the linkage from return to operation performance.

Consumer behavior does not directly affect reverse supply chain performance but operates through return intention as a mediating mechanism. Through return volume and variability return intention as the mediator explains how micro level psychological processes aggregates into macro level operational outcomes.

H3: Return intention mediates the relationship between behavioral drivers and reverse supply chain operational performance.

Traditional reverse supply chain design assumes exogenous and largely defect-driven returns. However behavioral-driven return requires adaptive designs that incorporates behavioral predictors into capacity planning and recovery strategies. Reverse supply chain accounting for behavioral return patterns are expected to outperform traditional design in efficiency and reliability.

H4: Reverse supply chain that incorporates behavioral return predictors outperforms traditional designs in terms of cost efficiency and service reliability.

Figure 3 lists down key variables in the behavioral-operational model and return intention is critical mediation variable to link the behavioral drivers with reverse supply chain performance. The outputs of behavioral drivers will be transformed into the input of reverse supply chain outcomes with analytical method. Solid arrows stands for hypothesized causal paths and dashed arrows stands for mediation effects.

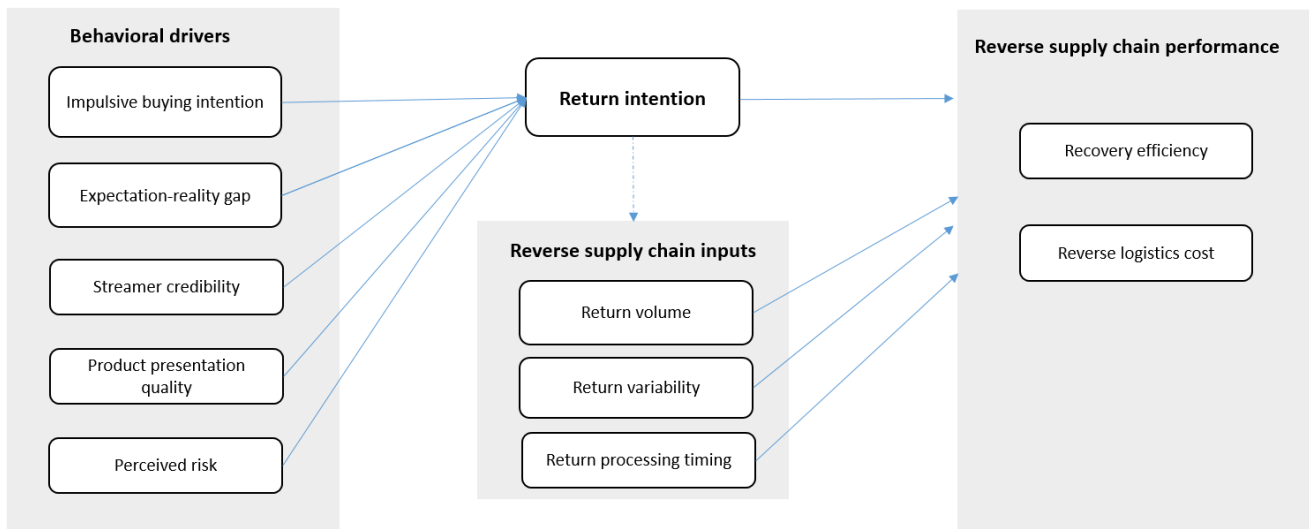


Figure 3. Hyperthetic model to list down key variables in the behavioral-operation model

Chapter 5 - Proposed research methodology or methodologies

5.1 Research Design

Live streaming commerce blends psychological, technological and logistic dynamics, so a mixed method for behavioral-operational approach is suggested to capture both human decision-making and operation performance consequences.

To achieve this objective, the study utilizes a two-stage empirical-analytical methodology:

1. Stage 1 : Behavioral Modeling

Using Structure Equation Modeling(SEM) to examine how consumer psychological drivers affect return intention in live streaming commerce. SEM is used mostly in the social and behavioral science fields to represent how various aspects of some phenomenon are thought to causally connect to one another. In this research different consumer behaviors occur simultaneously in one statistical estimation procedure, where all the model coefficients are calculated using all information from the observed variables. The SEM estimation will be more accurate than calculating each part of the model separately.

2 Stage 2: Reverse Supply Chain Operation Modedling

This study seeks to model the transformation of consumer return intention into realized return behavior within the context of live-streaming commerce. Because actual return behavior is operationalized as a binary outcome (returned = 1; not returned = 0), logistic regression is appropriate for binary decision modeling as it constrains predicted

probabilities to the interval [0,1] and does not assume normally distributed errors. The model is specified as:

$$\text{logit}(P(R_i = 1)) = \alpha + \beta RI_i + \sum_k \gamma_k X_{ik}$$

where RI_i represents return intention and X_{ik} denotes control variables. The coefficient β captures the sensitivity of return probability to return intention, thereby operationalizing the intention–behavior linkage central to this study. A positive and significant β indicates that stronger return intention increases the likelihood of realized returns.

The use of logistic regression is theoretically consistent with intention–behavior frameworks, which conceptualize action as a probabilistic realization of intention rather than a deterministic outcome. Moreover, the odds ratio (e^β) provides managerially interpretable insights, enabling the aggregation of predicted probabilities into expected return volumes and reverse supply chain demand. This interpretability is critical for translating behavioral findings into operational implications. Alternative methods were considered but deemed less suitable. Table 1 summarizes the methodological comparison –

Method	Suitability	Strengths	Limitations in This Study
Logistic regression	High	Models binary outcomes; interpretable β and odds ratios; probabilistic framework	Assumes logit functional form
Probit model	Moderate	Similar probabilistic structure	Less intuitive interpretation; no substantive advantage
Linear probability model	Low	Simple estimation	May predict invalid probabilities; heteroskedastic errors
Generalized SEM (binary outcome)	Moderate	Integrates latent and observed variables	Computationally complex; reduced transparency for operational aggregation
Machine learning classifiers (e.g., random forest)	Low for theory testing	High predictive accuracy	Black-box nature; lacks interpretable sensitivity parameter

Table 1. Comparison of Alternative Methods for Modeling Behavior–Action Transition

The behavioral-operational integration allows us to examine how consumer psychology directly influences reverse supply chain performance.

5.2 Behavioral Model (Survey + SEM)

To identify key behavioral drivers of return intention and quantify the strength of each antecedent, consumer sample survey is used for data collection and SEM is used for data analysis.

Sampling and data collection – on line questionnaire

- 1) Sampling size : target on line consumers (250-350 respondents) who shop through Douyin, TikTok Live, Taobao Live, etc
- 2) Sampling method: Online questionnaire with validated multi-item 7 point Likert scales.
- 3) Questionnaire design

Name							
Gender							
How many days from last shop							
Which live streaming commerce platform to shop							
Shop product category							
Return Rate							
Questionnaire	Strongly disagree	disagree	Slightly Disagree	Neutral	Slightly Agree	agree	Strongly agree
1.Impulsive buying behavior influences return intention							
2 Expectation-reality influences return intention							
3 Streamer/Anchor's credibility influences return intention							
4 Product presentation quality influences return intention							
5 Perceived product risk influences return intention							
6 Return policy leniency influences return intention when get the product in hand							

7. Consumer experience level influences return intention when watching the product presentation							
8 Product category complexity influences return rate when perceiving product risk							

Data analysis - Structure Equation Modeling (SEM)

Use SEM to analyze the data from on line questionnaire to describe the coefficients and significance from behavioral drivers to return intention. Some moderation variables will be also collected data in online questionnaire for future research.

The outputs of the SEM modeling will produce the critical output - Consumer Return Inention Score (RIS) as input to reverse supply chain (RSC) operation model

5.3 Reverse Supply Chain Operation Model (Logistic Regression + MLE)

This operation model analyzes how behaviors drive return flows and affect reverse supply chain performance in terms of key performance indicators ie processing time, capacity utilization, cost escalation etc. This process has discrete events and handles variability and randomness in return flow. So Logistic Regression with parameter assessment by Maximum Likelihood Estimate(MLE) is chosen to simulate real world operational constrains.

Mapping behavioral outputs to operational inputs

1) Converting behavioral scores into operation return rate

Reverse supply chain operates on return rates (percentage of purchased items that are returned). A regression or calibrated model converts RIS to expected return rate(RR):

$$\text{Return Rate(RR)} = \alpha + \beta \times \text{RIS}$$

α – baseline return rate of platform (e.g Douyin 20%-30%)

β - sensitivity multiplier calibrated by using pliot data

The expected return rate will be linked with behavioral consumer segments with low, medium and high return intent profiles. This is the most direct and widely accepted transformation

One example -

Segments	RIS Range	Expected Return Rate
Low	1-3	3%-5%
Medium	3-5	8%-12%
High	5-6	20%-35%
Extreme	6-7	40%-50%

2) Transforming behavioral variance into RSC variance

SEM outputs standard errors and residuals that indicate behavioral noise which could be mapped to product return arrival variability with statistics method.

3) Feeding the transformed variables into the RSC simulation

The simulation model needs below inputs :

a Return Arrivals - derived from RIS X behavioral variance

b Processing Times - derived from Expectation-Reality Gap, Perceived risk and presentation quality

c Capacity requirement - higher impulsive buying and Expectation-Reality Gap leads to more constrain in handling capacity

5.4 The integrated behavioral-operational Model

Finally the integrated behavioral-operational scenarios will be described as below

Return Intention Scenario	Inputs from Behavior	Results in RSC
Low	Low λ , low variance	Smooth capacity
Medium	Avg λ	Stable operation
High	High λ	Capacity constraint, delays
Extreme	Very High λ & variance	System failure

Chapter 6 - Data analysis plan

This research will adopt a two stage mixed-method approach so the data analysis will also follow two stage plan -

Stage 1: Quantitative behavioral survey among live-streaming consumers. Data will be analyzed using Structure Equation Modeling (SEM) to validate behavioral relationships. The Planned used software is AMOS or R. The following steps will be used in SEM analysis,

- 1) Data cleaning - remove incomplete responses (<60% completion) and handle the missing data
- 2) Likert scaling alignment – ensure all Likert scales(1-7) are aligned to avoid bias
- 3) Confirmatory Factor Analysis (CFA) – assess validity for each construct with convergent validity Factor loading > 0.60, AVE > 0.50 and composite reliability(CR) > 0.70 : Discriminant validity AVE > squared inter-construct correlations, HTML ratio <0.85.
- 4) Hypothesis test with SEM - output: Standardized beta coefficients, significance, Model R2 values

Stage 2: Simulation and optimization modeling of reverse supply chain incorporating behavioral output data (return intention score). Data will be analyzed using Logistic Regression with parameter assessment from maximum likelihood estimation(MLE) to test the operation design efficiency. A company's LCS real return data will be used for simulation.

The final hypothesis will be tested and concluded after two stage data analysis.

Chapter 7 - Expected results and managerial recommendations

This research is targeted to explore the behavior linkage with reverse supply chain performance in live streaming commerce from the integrated behavioral-operational framework. Finally the research results could clarify the behavioral drivers for reverse supply chain design elements and further optimize the supply chain efficiency. From the theoretical, methodological and practical view point, the research will result in below outcomes and managerial recommendation -

1. Theoretical: Introduce a novel behavioral–operational framework in reverse supply chain and clarify the relationship between behavioral drivers and reverse supply chain performance. The coefficient among different factors are studied to test hypothesis and build the linkage.
2. Methodological: Combine behavioral modeling (SEM) with reverse supply chain simulation (Logistic regression) to transform the behavioral inputs to operational outputs. This modeling method is innovative to link psychological drivers with operational quantitative variance.
3. Practical: Offer data-driven insights for live streaming commerce platform and company to design cost and time efficient return system. In the real world the return flow management capability and performance could be competitive advantage for the brand to win the business success in the fierce marketplace competition.

LSC is becoming one of the largest e-commerce channel in many product categories, ie clothes, cosmetics etc and still keeps very strong growth in the global wide. LSC business success depends on the capability to control marketing investment and total product delivery cost. As one of the most significant and uncertain cost element, the product return management efficiency is critical for management's consideration. So every business owner cares more about how to control the return rate and achieve the reasonable cost efficiency. This research and the proposed behavioral-operational framework will help the management to reframe the strategic thinking on product return and make decision across the whole business to achieve best fitting return management capability. Below list down key insights and contributions to managerial recommendation –

- 1) Product return in live streaming commerce should be considered as strategic outcome of consumer behavior rather than an unavoidable operational cost. So incorporating the behavioral metrics into return forecast will significantly improve forecast accuracy beyond traditional data driven mechanism.
- 2) Real time behavioral data from live streaming session should help to plan better reverse supply chain capability. From the behavioral analysis the early warning system, reverse logistics preallocation and flexible labor scheduling could be established to better support live streaming activity.
- 3) Live streaming commerce success should have a good balance between business success(more sales) and operation efficiency(reseasonal cost and service). Establishing

cross function planning process and shared KPIs (ie return rate, recovery efficiency) will better enable business success and cross functional collaboration to win this critical business.

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