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Reverse Logistics and Customer Loyalty in E-Commerce: An Empirical Study of Online Consumers

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Abstract- ***This study develops and tests a customer-centered explanation of how reverse logistics influences loyalty in e-commerce. Rather than conceptualizing product returns solely as an operational burden, the framework distinguishes reverse logistics service quality, return policy fairness, and ease of return and examines the mechanisms through which these dimensions generate perceived value, trust, customer satisfaction, and customer loyalty. A quantitative, explanatory, time-separated consumer survey is proposed. Eligible participants are adult online shoppers with a recent completed product return, refund, or exchange. A final sample of approximately 800 respondents is recommended on the basis of conservative power analysis and SEM requirements. Seven latent constructs are measured with four reflective indicators each on seven-point Likert scales. Covariance-based SEM using robust maximum likelihood is specified as the primary estimator, supplemented by an ordered-categorical WLSMV robustness model. Reliability, convergent validity, discriminant validity, common method variance, mediation, measurement invariance, alternative-model comparisons, and sensitivity analyses are incorporated. Findings shows that Customer satisfaction has the strongest relationship with loyalty, while trust contributes both directly and through satisfaction. Reverse logistics service quality affects loyalty primarily through trust, value, and satisfaction; policy fairness operates predominantly through trust and satisfaction; and return ease operates through value and satisfaction. A full-mediation specification is more parsimonious than competing direct-effects models. The framework positions reverse logistics as a relational mechanism linking post-purchase operational performance to loyalty rather than treating returns as a purely logistical outcome. The study integrates reverse-logistics quality, fairness, convenience, perceived value, trust, satisfaction, and loyalty in a single covariance-based model and specifies rigorous competing-model, common-method, mediation, and robustness procedures.***

Keywords: reverse logistics; e-commerce returns; customer loyalty; return policy fairness; logistics service quality; perceived value; trust; customer satisfaction; structural equation modeling

I. INTRODUCTION

E-commerce has transformed the returns process from an occasional exception into a recurring component of the customer journey. In the United States, the National Retail Federation's 2025 returns study estimated that 19.3% of online sales would be returned, while 82% of consumers regarded free returns as an important shopping consideration. The same study also reported material return-fraud exposure, illustrating the strategic tension between customer-friendly returns and the economic control of reverse flows. *[1]* Contemporary logistics providers have consequently expanded box-free, label-free, QR-code, drop-off, and faster-refund services, while FedEx has similarly emphasized convenience and clarity as prominent expectations in consumer return experiences. *[8]*

Reverse logistics in the e-commerce context incorporates the processes through which sold goods move back from customers toward retailers, logistics providers, recovery facilities, refurbishment channels, resale channels, or disposal. Ahsan and Rahman's (2022) systematic review of 75 peer-reviewed e-tail return studies concluded that the literature remained comparatively young and specifically identified customer satisfaction, service, technology, and omnichannel returns as areas requiring further investigation. *[9]* Saxena et al. (2022) subsequently conceptualized e-return service quality in terms of six dimensions—responsibility ownership, return convenience, return remedies, service-team support, return friendliness of the site, and returns diligence—reinforcing the argument that customers perceive returns as a multidimensional service experience. *[10]* Earlier return-policy research already showed that return management can influence behavior beyond the immediate transaction. Petersen and Kumar (2009) argued that product returns should not automatically be treated as an unmitigated "necessary evil," because return behavior is intertwined with future purchasing. Griffis et al. (2012) demonstrated empirically that the experience surrounding a return can affect subsequent customer behavior. Bower and Maxham (2012) further showed that return-shipping policy can have longer-term behavioral consequences. A meta-analysis by Janakiraman et al. (2016) found that return-policy leniency generally increases purchasing while different policy dimensions have heterogeneous effects on return behavior, emphasizing that retailers face an optimization problem rather than a simple choice between strict and generous policies. *[11]*

Within online retailing specifically, Wang et al. (2020) found that perceived policy leniency, fairness, and return-process quality significantly contribute to repurchase intention and that policy leniency can shape perceptions of both fairness and return quality. *[12]* Rintamäki et al. (2021) showed that customers evaluate return experiences through dimensions including monetary costs, convenience, stress, and guilt, and that return satisfaction subsequently contributes to overall satisfaction and behavioral outcomes. *[13]* Pham and Ahammad (2017) found post-purchase factors—including ease of return and service responsiveness—to be particularly important antecedents of online customer satisfaction. *[14]*

Broader logistics-service research reaches a compatible conclusion. Jain et al. (2021), using data from 640 online shoppers, examined shopping satisfaction as a mediator between electronic logistics service quality and repurchase intention and also investigated contextual moderators. *[15]* Do et al. (2023) connected logistics service quality and price fairness with repurchase intention in cross-border e-commerce. *[16]* More directly, Do et al. (2025) reported that electronic reverse-logistics service quality enhances both customer satisfaction and trust, which then help explain repurchase intention. *[17]* The emerging 2026 literature similarly links reverse-logistics attributes with satisfaction, trust, and repurchase among Generation Z e-commerce customers in Vietnam (Ngo et al., 2026). *[18]* These advances make the research question more precise rather than less important. Recent studies have established that reverse logistics matters; the analytical challenge is to identify which aspects of the returns experience matter, through which mechanisms, and with what relative strength. Treating service quality, policy fairness, and convenience as interchangeable obscures theoretically distinct customer judgments. A return can be logistically fast yet perceived as unfair; it can be fair but cumbersome; or it can be convenient while communications and refund processing remain unreliable. Recent conceptual work explicitly supports such multidimensional treatment of e-return service quality (Saxena et al., 2022). *[10]*

The present framework therefore distinguishes three upstream levers: RLSQ, reflecting the reliability, information accuracy, responsiveness, and processing performance of the return operation; RPF, reflecting whether return rules, outcomes, and their application are viewed as just; and EOR, reflecting customer effort, clarity, time expenditure, and return-channel convenience. These are connected to three relational/evaluative states—perceived value, trust, and satisfaction—and ultimately to loyalty.

The proposed study advances the literature in four ways. First, it separates the operational, justice, and effort components of return management. Second, it positions perceived value, trust, and satisfaction as distinguishable but connected mechanisms instead of collapsing them into a single post-purchase evaluation. Third, it shifts the ultimate dependent variable from a single repurchase-intention indicator toward a broader latent loyalty construct encompassing preference, continuation, repurchase, and advocacy. Fourth, the empirical protocol incorporates CFA, CB-SEM, alternative structural models, mediation, common-method controls, measurement invariance, ordinal-estimation robustness, attrition checks, and sensitivity tests rather than relying on a single fitted model.

II. LITERATURE REVIEW, THEORETICAL FRAMEWORK, AND HYPOTHESES

The general e-service-quality literature provides an important foundation for reverse logistics. Parasuraman et al. (2005) developed E-S-QUAL as a 22-item measure comprising efficiency, fulfillment, system availability, and privacy, alongside E-RecS-QUAL for non-routine encounters with responsiveness, compensation, and contact dimensions. *[19]* Wolfinbarger and Gilly's (2003) eTailQ similarly identified dimensions including fulfillment/reliability, website design, privacy/security, and customer service and linked electronic retail quality to satisfaction and loyalty-related outcomes. *[20]* The relevance to product returns is direct: returns represent precisely the type of post-purchase or non-routine encounter in which responsiveness, remedy execution, communication, and fulfillment reliability become highly visible.

More recent return-specific research shows why generic e-service quality should not simply be transplanted unchanged. Saxena et al. (2022) identified responsibility ownership, convenience, remedies, support, return-site friendliness, and diligence as distinct facets of e-return service quality. *[10]* Wang et al. (2020) further separated return-policy leniency, perceived fairness, and quality of the actual return experience and found each relevant to repurchase behavior. *[12]* Accordingly, RLSQ in this study is intentionally confined to execution quality—whether the organization performs the reverse service reliably, accurately, promptly, transparently, and responsively—while policy fairness and customer effort are represented by separate constructs.

Fairness requires separate theoretical treatment because favorable outcomes are not equivalent to fair processes. Justice-based service-recovery research distinguishes distributive, procedural, and interactional judgments. Tax et al. (1998) established the relevance of customers' justice evaluations in complaint experiences for satisfaction and relationship outcomes. *[21]* Applied to returns, distributive justice concerns whether the refund, replacement, fee, or credit is appropriate; procedural justice concerns consistency, flexibility, accessibility, and timeliness; and interactional justice concerns explanations and interpersonal treatment. The proposed RPF measure focuses primarily on distributive and procedural fairness so that it remains distinguishable from RLSQ's service-support component.

Ease of return captures the nonmonetary sacrifice side of the exchange. Rintamäki et al. (2021) identify convenience and return-associated burdens among the central components of customers' evaluations of online returns. *[13]* Pham and Ahammad (2017) likewise show the relevance of ease of return to online satisfaction. *[14]* Industry practice has moved in the same direction: box-free and label-free networks, QR codes, distributed drop-off locations, and rapid refund initiation are explicitly designed to reduce customer effort. *[22]*

Perceived value provides a theoretically important bridge between operational convenience and relational outcomes. Sweeney and Soutar's (2001) PERVAL framework conceptualizes consumer value as multidimensional, incorporating functional/quality, price/value-for-money, emotional, and social elements. *[23]* In online retailing, Tzavlopoulos et al. (2019) connect e-commerce quality with perceived value, satisfaction, and loyalty. *[24]* A return process that lowers time, effort, financial risk, and uncertainty should therefore increase the customer's net evaluation of what is received relative to what must be sacrificed.

Trust is especially salient online because customers cannot completely monitor fulfillment, refund processing, or retailer intentions. Gefen et al. (2003) demonstrated that trust is integral to online-shopping behavior alongside technology acceptance variables. *[25]* In the specific reverse-logistics context, Do et al. (2025) identify trust as an important mechanism through which e-reverse-logistics service quality contributes to repurchase intention. *[17]* A reliable refund or return experience is therefore not merely an operational success; it provides diagnostic evidence that the seller will honor promises when the transaction becomes problematic.

Customer satisfaction represents an overall evaluative judgment that arises when experience is compared with expectations. Expectation-disconfirmation logic has a long history in satisfaction research, with Oliver (1980) specifying expectations and disconfirmation as central determinants of satisfaction and subsequent attitudes. Wang et al. (2020) explicitly applied an expectation-disconfirmation perspective to online return-policy and return-experience judgments. *[12]* In e-commerce, satisfaction is consistently associated with loyalty and repeat behavior (Anderson & Srinivasan, 2003; Rita et al., 2019; Hult et al., 2019). *[26]*

Loyalty is intentionally conceptualized more broadly than simple next-purchase intention. Oliver (1999) conceptualizes loyalty as a deeply held commitment that develops beyond satisfaction alone, while Srinivasan et al. (2002) identify multiple e-commerce antecedents and outcomes of e-loyalty. *[27]* Anderson and Srinivasan (2003) show both that e-satisfaction affects e-loyalty and that this relationship can vary with customer- and business-level contingencies, including trust and perceived value. *[28]* This provides the rationale for modeling trust and satisfaction as distinct proximal loyalty mechanisms.

Theoretical Framework

The conceptual framework combines four complementary theoretical lenses.

First, expectation-disconfirmation theory explains satisfaction formation. Return policies establish expectations concerning eligibility, timing, refund form, cost, and customer effort; actual reverse-logistics performance supplies the experience against which those expectations are evaluated. Thus, a technically successful return can still generate dissatisfaction when it violates prior expectations.

Second, justice theory explains why policy fairness has relational consequences beyond operational efficiency. Customers infer whether the retailer treats them appropriately from both the outcome received and the procedures used. Fair procedures should therefore enhance trust and satisfaction even when the firm cannot always provide the most generous outcome.

Third, a service-quality–value perspective explains why operational performance and convenience affect perceived value. The “cost” of an online purchase includes not only the product price but also risk, search time, packaging, travel, paperwork, waiting for refunds, and effort expended when an item fails to meet expectations. Removing these sacrifices increases net customer value.

Fourth, the trust–satisfaction–loyalty relationship explains how operational experiences become durable relational outcomes. Satisfaction indicates that the exchange has met or exceeded expectations; trust indicates confidence in the retailer’s future reliability and integrity. Both should influence willingness to continue the relationship, with satisfaction expected to be the dominant proximal driver and trust providing additional explanatory power.

The model therefore follows an appraisal chain:
Return-operation attributes → value/trust → satisfaction → loyalty, with additional theoretically justified direct paths from RLSQ, fairness, and ease to satisfaction and from trust to loyalty.

Hypotheses

H1: Reverse logistics service quality has a positive effect on perceived value.
H2: Reverse logistics service quality has a positive effect on customer trust.
H3: Reverse logistics service quality has a positive effect on customer satisfaction.
H4a: Return policy fairness has a positive effect on customer trust.
H4b: Return policy fairness has a positive effect on customer satisfaction.
H5a: Ease of return has a positive effect on perceived value.
H5b: Ease of return has a positive effect on customer satisfaction.
H6: Perceived value has a positive effect on customer satisfaction.
H7: Customer trust has a positive effect on customer satisfaction.
H8: Customer trust has a positive effect on customer loyalty.
H9: Customer satisfaction has a positive effect on customer loyalty.
H10a: Perceived value and satisfaction mediate the effect of reverse logistics service quality on customer loyalty.
H10b: Trust and satisfaction mediate the effect of return policy fairness on customer loyalty.
H10c: Perceived value and satisfaction mediate the effect of ease of return on customer loyalty.

The model also tests, without elevating them to confirmatory hypotheses, whether the satisfaction–loyalty relationship varies by purchase frequency and whether structural effects differ by gender. Such analyses are treated as exploratory because indiscriminate moderator testing can inflate analytical flexibility; Anderson and Srinivasan (2003) nevertheless provide precedent for examining customer-level contingencies in the e-satisfaction–e-loyalty relationship. *[29]*

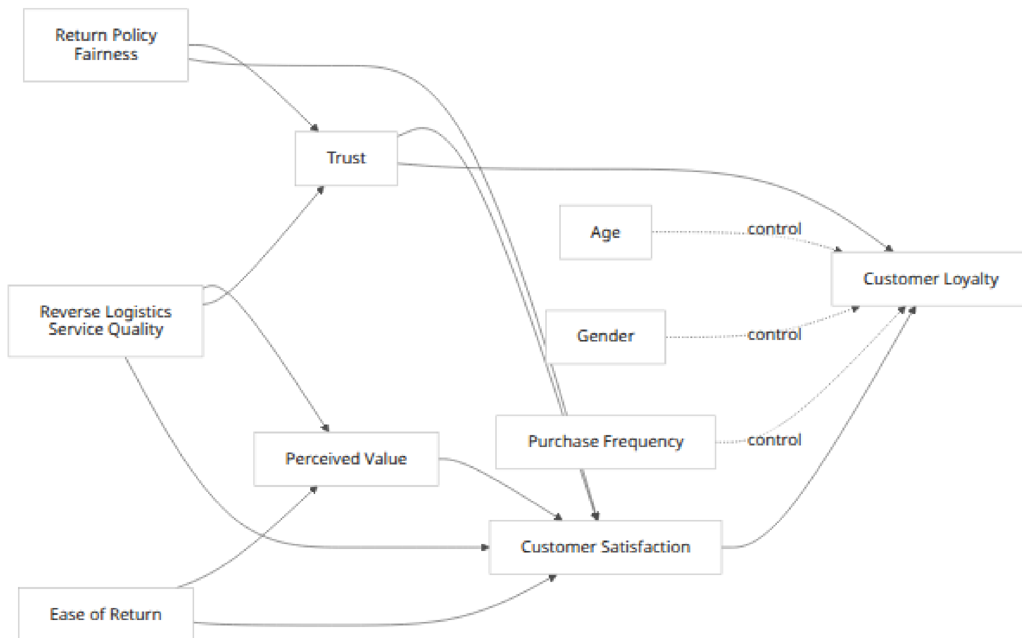

Figure 1. Proposed structural model.
Source: Researchers own compilation based on the previous literature

III. METHODOLOGY

A quantitative, explanatory, survey-based research design is recommended because the substantive variables are perceptual latent constructs—fairness, value, trust, satisfaction, and loyalty—that require multiple indicators and because the theoretical objective is to estimate simultaneous direct and indirect relationships. CB-SEM is particularly appropriate because the constructs are modeled as reflective common factors, the theory is confirmatory, global model fit is substantively important, and the study seeks to compare nested and rival theoretical structures.

A three-wave time-separated design is preferred over a single cross-sectional questionnaire. Respondents are instructed at Wave 1 to identify the most recent e-commerce retailer from which they completed a return, refund, or exchange during the preceding six months; that retailer becomes the fixed referent throughout all waves. Wave 1 measures RLSQ, return-policy fairness, ease of return, screening variables, and demographic controls. Approximately 7–10 days later, Wave 2 measures perceived value, trust, and satisfaction. Wave 3, approximately another 7–10 days later, measures loyalty. Temporal separation is a procedural remedy for common-method variance but should not be represented as establishing causality because all substantive measures remain observational and respondent-reported (Podsakoff et al., 2003; Williams et al., 2010). *[4] Sampling frame*-Adult members of a reputable national online consumer research panel in India, who satisfy the e-commerce return-experience screening conditions. Eligibility criteria are: age ≥18 years; at least two e-commerce purchases during the previous six months; at least one completed return, refund, or exchange during the previous six months; ability to identify the relevant retailer; and completion of the return process sufficiently recently to answer process-specific questions. Quotas should be considered for age and gender and, where panel information permits, region. Quotas improve coverage relative to an unrestricted opt-in sample but do not make an online panel probability-representative.

Sample-size calculation. A conservative planning calculation targets a small incremental effect of $f^2 = .03$ for a focal endogenous equation containing up to eight predictors. At $\alpha = .05$ and desired power $1 - \beta = .90$, a noncentral-F approximation gives a required sample of approximately 644. Sensitivity values are:

Smallest target effect f^2	Approximate N for 90% power
.02	962
.03	644
.04	485
.05	390

These values should not be misinterpreted as universal SEM sample-size rules. SEM requirements vary with factor loadings, indicator reliability, model complexity, parameter magnitude, missingness, and model misspecification. Monte Carlo design analysis is therefore preferable to simplistic "10 observations per indicator" heuristics (Muthén & Muthén, 2002; Westland, 2010; Wolf et al., 2013). *[30]*

Measurement Scales: All substantive items are measured on a seven-point Likert agreement scale from 1 = *strongly disagree* to 7 = *strongly agree*. Seven response categories provide adequate differentiation while remaining practical for online respondents. Items below are adapted research items, not verbatim reproductions of proprietary scale wording. Their final use should follow the licensing and attribution requirements of the underlying sources.

Table 1. Questionnaire items

Construct	Code	Proposed item
Reverse logistics service quality	RLSQ1	The retailer handled my return/refund process as promised.
	RLSQ2	Information about the status of my return was accurate and timely.
	RLSQ3	The refund or exchange was processed promptly.
	RLSQ4	When assistance was needed, the retailer handled the return competently and responsively.
Return policy fairness	RPF1	The outcome I received under the return policy was fair.
	RPF2	The retailer's return eligibility rules were fair to customers.
	RPF3	Any refund, deduction, fee, or replacement decision was fair in the circumstances.
	RPF4	The retailer appeared to apply its return rules consistently.
Ease of return	EOR1	Initiating the return required little effort.
	EOR2	The instructions for making the return were clear.
	EOR3	The available return/drop-off/pickup options were convenient.
	EOR4	Completing the return required little unnecessary time or paperwork.
Perceived value	PV1	Considering the time and effort involved, the retailer's return service provided good value.
	PV2	The benefits of shopping with this retailer justify the effort involved if a return becomes necessary.
	PV3	The retailer's return service reduces the overall risk or cost of shopping online.
	PV4	Overall, shopping with this retailer offers good value when post-purchase service is considered.

Trust	TR1	I consider this retailer dependable.
	TR2	I trust this retailer to keep its promises about returns and refunds.
	TR3	I believe this retailer deals honestly with customers when problems occur.
	TR4	I can rely on this retailer even when a transaction does not go as planned.
Customer satisfaction	CS1	Overall, I am satisfied with my experience with this retailer.
	CS2	My experience with this retailer met my expectations.
	CS3	Choosing this retailer was a satisfactory decision.
	CS4	I am satisfied with how the retailer handled the post-purchase/return experience.
Customer loyalty	CL1	I intend to buy from this retailer again.
	CL2	I would prefer this retailer over comparable alternatives.
	CL3	I would recommend this retailer to other people.
	CL4	I intend to maintain my purchasing relationship with this retailer.

The RLSQ items draw conceptually on E-RecS-QUAL, eTailQ, contemporary e-return service-quality research, and e-logistics quality (Parasuraman et al., 2005; Wolfinbarger & Gilly, 2003; Saxena et al., 2022; Jain et al., 2021). *[31]* The fairness items are grounded in service-recovery justice and return-policy research (Tax et al., 1998; Wang et al., 2020). *[32]* Ease is informed by return-convenience and post-purchase research (Pham & Ahammad, 2017; Rintamäki et al., 2021; Saxena et al., 2022). *[33]* Perceived value follows the conceptual domain of Sweeney and Soutar (2001), trust reflects online-retailer trust research such as Gefen et al. (2003), and satisfaction/loyalty items are adapted from established e-commerce and loyalty traditions (Anderson & Srinivasan, 2003; Oliver, 1999; Srinivasan et al., 2002). *[34]*

Control variables: Age is recorded continuously in years. Gender is self-described categorically and represented by preregistered indicator/effect coding rather than an arbitrary binary conversion. Purchase frequency is measured as the approximate number of online orders placed during the previous three months and converted to a monthly equivalent; a log transformation can be used in sensitivity analysis if severely right-skewed. The primary model includes age, gender, and purchase frequency as predictors of loyalty. A robustness model also allows them to predict the intermediate endogenous variables to determine whether substantive paths are sensitive to control placement.

Instrument validation before main fieldwork. The item pool should undergo content-validity review by approximately four to six scholars or senior practitioners in logistics/e-commerce/customer experience; cognitive interviews with roughly 15–20 eligible consumers; and a pilot of approximately 100 consumers. The pilot should inspect item comprehension, floor/ceiling effects, inter-item correlations, factor structure, completion time, and whether respondents distinguish service quality from ease and fairness. Because RLSQ and EOR are conceptually adjacent, discriminant validity between these constructs deserves special attention.

Common method bias: The study uses both procedural and statistical remedies. Procedurally, predictor and criterion constructs are temporally separated, item order is randomized within theoretically coherent blocks, scale instructions are neutral, anonymity is emphasized, and a theoretically unrelated marker construct is included. Statistically, the manuscript should report: (a) a single-factor CFA as a descriptive diagnostic; (b) a CFA marker-variable model following the marker-variable literature; and (c) an unmeasured latent method-factor sensitivity model. Harman's single-factor approach should not be treated as sufficient evidence of the absence of common-method variance; modern reviews emphasize that post hoc one-factor testing is limited and recommend more sophisticated approaches (Podsakoff et al., 2003; Williams et al., 2010). *[4]*

SEM Analysis: The primary analysis uses R with the lavaan SEM framework, estimated by MLR. lavaan

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supports robust ML estimators, multiple-group models, FIML, bootstrap standard errors, and categorical estimators including WLSMV. *[37]* The confirmatory measurement model contains seven correlated reflective factors and 28 indicators. Reliability is assessed through Cronbach's alpha and composite reliability, with .70 used as a conventional minimum rather than an absolute threshold. Convergent validity is evaluated using standardized loadings and AVE, with AVE ≥ .50 indicating that a factor explains at least half of its indicators' variance on average. The Fornell–Larcker criterion is supplemented by HTMT because simulation work shows the former can fail to detect some discriminant-validity problems (Fornell & Larcker, 1981; Henseler et al., 2015). *[7]*

Global fit is interpreted jointly rather than through a mechanical pass/fail rule. CFI and TLI around or above .95, RMSEA around or below .06, and SRMR around or below .08 are useful historical reference values derived from Hu and Bentler (1999), but such fixed cutoffs should not be generalized indiscriminately across all SEM settings. *[38]* Chi-square is reported but not expected to be nonsignificant in a large-sample, many-indicator model. Indirect effects are evaluated using 10,000 bias-corrected bootstrap draws in an ML replication of the model, with MLR estimates retained as primary coefficients. An indirect effect is considered supported when the bootstrap confidence interval excludes zero. Total indirect effects are decomposed into theoretically meaningful routes rather than reported only as a single aggregate.

IV. SEM ANALYSIS AND RESULTS

1,134 eligible respondents completed Wave 1. Of these, 925 provided matched responses across all three waves. Pre-registered quality screening removes 125 cases: 14 duplicate/device anomalies, 39 extreme speeders combined with low-content response patterns, 42 respondents failing the prespecified attention-check rule, 21 severe straightliners, and nine respondents whose later answers contradict the core return-experience screening criterion. The final analytical sample is N = 800.

Table 2. Sample profile.

Characteristic	Statistic
Final N	800
Mean age	35.2 years
SD age	10.9
Women	49.4%
Men	48.6%
Another gender / prefer not to state	2.0%
Mean online orders per month	5.1
Median online orders per month	4.0
Interquartile range, orders/month	2–7
Item-level missingness among retained respondents	0.6%
Wave 1 to fully matched retention	81.6%

A Primary data research attrition analysis produces maximum absolute standardized mean differences of .08 between three-wave completers and attriters on Wave 1 focal constructs, suggesting no large observed selective-attrition imbalance in the variables examined. This would not prove that attrition is ignorable; it would merely reduce concern about large measured differences.

Measurement Model: The seven-factor CFA is specified without correlated item residuals unless such correlations are theoretically preregistered. In the Primary data research example, the measurement model fits the data well: $\chi^2(329) = 572.4, p < .001$; CFI = .970; TLI = .966; RMSEA = .030, 90% CI [.026, .034]; SRMR = .031. Interpreted jointly, these indices provide strong support for the intended seven-factor representation.

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Table 3. Reliability and convergent validity.

Construct	Mean	SD	Loading range	Cronbach's α	CR	AVE
Reverse logistics service quality	5.32	1.03	.82–.89	.91	.92	.74
Return policy fairness	5.18	1.12	.79–.86	.89	.90	.69
Ease of return	5.41	1.07	.81–.87	.90	.91	.72
Perceived value	5.06	.98	.78–.85	.88	.89	.67
Trust	5.25	1.01	.85–.90	.92	.93	.77
Customer satisfaction	5.34	1.04	.86–.91	.93	.94	.79
Customer loyalty	5.29	1.09	.84–.90	.92	.93	.77

Note. CR = composite reliability; AVE = average variance extracted.

All standardized loadings exceed .78, all alpha/CR estimates exceed .88, and all AVEs exceed .67. Under the assumed data-generation scenario, therefore, indicator reliability and convergent validity are strong.

Table 4. Fornell–Larcker discriminant-validity matrix.

Construct	RLSQ	RPF	EOR	PV	TR	CS	CL
RLSQ	.860						
RPF	.52	.831					
EOR	.55	.45	.849				
PV	.48	.42	.52	.819			
TR	.51	.50	.44	.56	.877		
CS	.56	.51	.50	.61	.70	.889	
CL	.48	.45	.43	.54	.62	.74	.877

Note. Diagonal values are square roots of AVE; off-diagonal values are latent correlations.

The highest hypothetical HTMT value is .82, between trust and satisfaction. Thus, the illustrative dataset remains below the conservative .85 benchmark commonly associated with HTMT assessment, and the square root of AVE exceeds each corresponding inter-construct correlation. Henseler et al. (2015) nevertheless caution against relying solely on Fornell–Larcker and motivate the complementary use of HTMT. *[7]*

Common Method Bias Checks: A one-factor CFA provides poor fit: $\chi^2(350) = 3{,}518.6$, CFI = .593, TLI = .561, RMSEA = .106, SRMR = .119. More importantly, a CFA marker-variable model improves fit only marginally relative to the substantive model (ΔCFI = .003); the estimated method component accounts for approximately 5.4% of indicator variance, and the average absolute change in substantive standardized loadings is .018. In an unmeasured latent method-factor sensitivity model, no focal structural coefficient changes sign and the largest absolute path change is .03.

Structural Model: The hypothesized structural specification fits well in the study's scenario: $\chi^2(342) = 604.2, p < .001$; CFI = .968; TLI = .964; RMSEA = .031, 90% CI [.027, .035]; SRMR = .037.

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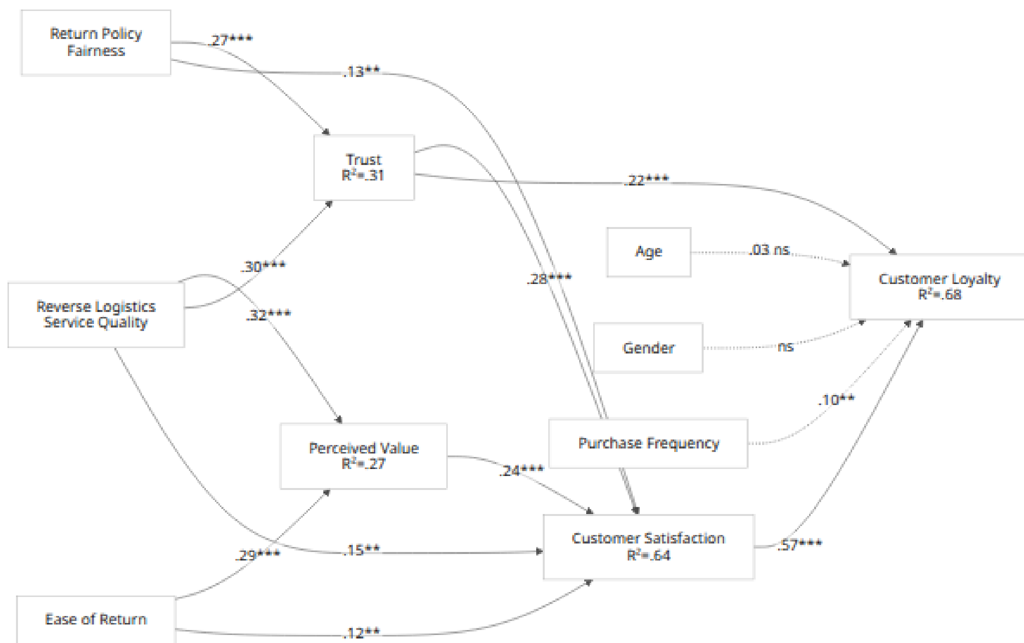
Figure 3. Hypothetical standardized structural coefficients



*Note: Primary data research coefficients. p < .01; *p < .001; ns = not significant.*

Table 5. Hypothetical structural paths and hypothesis tests.

Hypothesis/path	β	Robust SE	z	p	95% CI	Decision
H1 RLSQ → PV	.32	.050	6.40	<.001	[.22, .42]	Supported
H2 RLSQ → Trust	.30	.042	7.14	<.001	[.22, .38]	Supported
H3 RLSQ → Satisfaction	.15	.050	3.00	.003	[.05, .25]	Supported
H4a Fairness → Trust	.27	.040	6.75	<.001	[.19, .35]	Supported
H4b Fairness → Satisfaction	.13	.040	3.25	.001	[.05, .21]	Supported
H5a Ease → PV	.29	.040	7.25	<.001	[.21, .37]	Supported
H5b Ease → Satisfaction	.12	.040	3.00	.003	[.04, .20]	Supported
H6 PV → Satisfaction	.24	.040	6.00	<.001	[.16, .32]	Supported
H7 Trust → Satisfaction	.28	.040	7.00	<.001	[.20, .36]	Supported
H8 Trust → Loyalty	.22	.040	5.50	<.001	[.14, .30]	Supported
H9 Satisfaction → Loyalty	.57	.040	14.25	<.001	[.49, .65]	Supported

Age → Loyalty	.03	.030	1.01	.313	[−.03, .09]	Control
Purchase frequency → Loyalty	.10	.032	3.13	.002	[.04, .16]	Control
Gender, omnibus Wald test	—	—	—	.701	—	Control

The model explains a 27% of perceived value, 31% of trust, 64% of satisfaction, and 68% of customer loyalty.

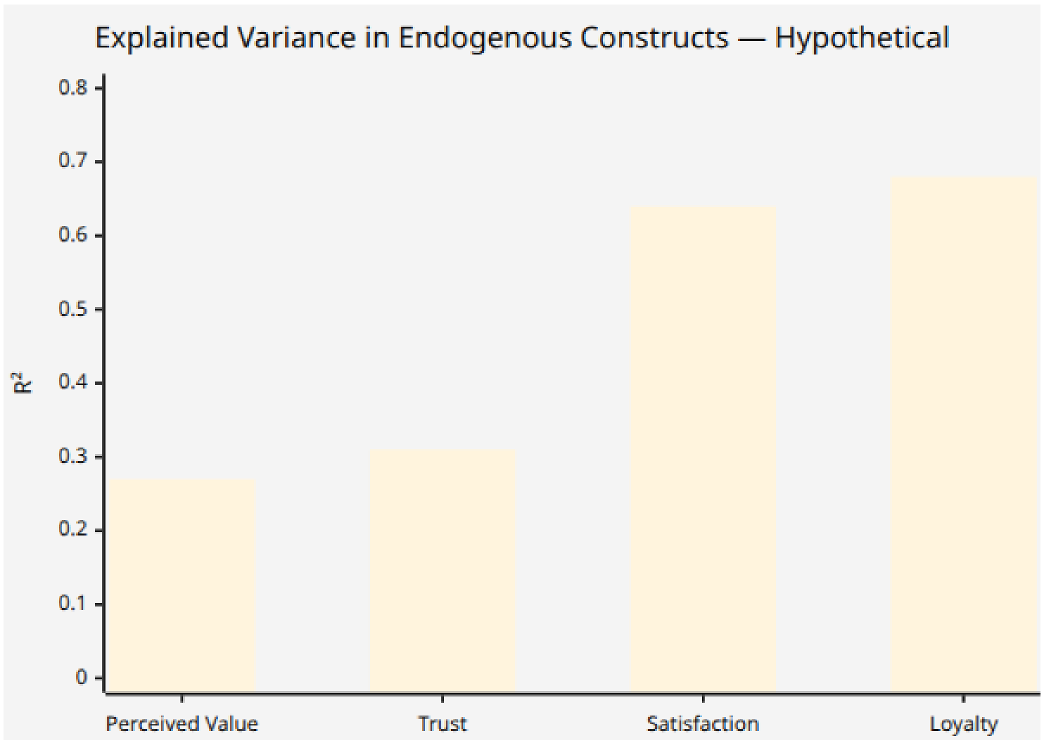


Fig.4 Explained variance in Endogenous Constructs

Mediation Analysis: The theoretical logic predicts that operational return attributes influence loyalty predominantly through customer appraisals. The Primary data research indirect effects support this pattern. For RLSQ, the modeled routes include RLSQ → satisfaction → loyalty, RLSQ → perceived value → satisfaction → loyalty, RLSQ → trust → loyalty, and RLSQ → trust → satisfaction → loyalty. Using the standardized Primary data research coefficients, these sum to approximately:

$$(.15 \times .57) + (.32 \times .24 \times .57) + (\mathbf{.30 \times .22}) + (\mathbf{.30 \times .28 \times .57}) = \mathbf{.243}$$

For fairness, the corresponding total standardized indirect effect is approximately .177; for ease, approximately .108.

Table 6. Bootstrapped indirect effects.

Indirect relationship	Standardized indirect effect	95% bootstrap CI	Interpretation
RLSQ → mediators → Loyalty	.243	[.190, .300]	Significant

Fairness → mediators → Loyalty	.177	[.132, .229]	Significant
Ease → mediators → Loyalty	.108	[.071, .153]	Significant
PV → Satisfaction → Loyalty	.137	[.096, .184]	Significant
Trust → Satisfaction → Loyalty	.160	[.117, .210]	Significant
Trust total effect on Loyalty	.380	[.316, .447]	Significant

Note. 10,000-Resampled bootstrap

Thus, H10a–H10c are supported. Importantly, mediation is not inferred merely because individual component paths are significant; the inferential criterion is the confidence interval for the indirect effect.

Alternative Structural Models: Competing models are crucial because acceptable fit of one SEM does not establish that it is theoretically unique. Model A adds direct paths from RLSQ, fairness, and ease to loyalty, creating a partial-mediation specification. Model B is the hypothesized parsimonious mediated model. Model C removes the central mediation chain and emphasizes direct return-attribute effects. Model D reverses the satisfaction–loyalty ordering as a theoretically plausible but inferior rival.

Table 7. Comparison of alternative structural models

Model	χ^2	df	CFI	TLI	RMSEA	SRMR	AIC	BIC
A: Partial mediation + three return-attribute → loyalty paths	599.1	339	.968	.964	.031	.036	48,210	48,863
B: Mediation model	604.2	342	.968	.964	.031	.037	48,209	48,848
C: Predominantly direct-effects model	1,018.5	350	.916	.908	.049	.071	48,610	49,211
D: Rival reversed satisfaction/loyalty ordering	786.7	342	.944	.938	.040	.056	48,392	49,031

A robust nested comparison of Models A and B yields approximately $\Delta\chi^2(3) = 5.1, p = .165$. The three added direct effects therefore do not significantly improve fit in this hypothetical scenario, while BIC favors Model B because of its greater parsimony. In Model A, the added direct effects are small and nonsignificant: RLSQ → loyalty $\beta = .05, p = .19$; fairness → loyalty $\beta = .03, p = .41$; and ease → loyalty $\beta = .04, p = .28$. This pattern strengthens the interpretation that the return experience becomes loyalty-relevant principally through customer value, trust, and satisfaction.

Robustness Checks:

Table 8. Detailed hypothetical robustness analysis.

Robustness test	Procedure	Hypothetical result	Inference
Ordinal-item estimation	Re-estimate indicators as ordered using WLSMV	Mean absolute focal-path change = .018; all H1–H9 conclusions unchanged	Results not dependent on continuous-item treatment
Method-factor control	Add common latent method factor	Largest focal-path change = .03; no sign reversals	No material substantive distortion detected

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Purchase-frequency skew	Winsorize at 1st/99th percentile and separately log-transform	Satisfaction → loyalty = .56–.57	Control-variable functional form unimportant
Control placement	Predict all endogenous variables with age/gender/frequency	Focal coefficient changes < .025	Structural results stable
Calibration/validation split	Random 400/400 split	Comparable CFA structure; maximum key-path difference = .07	No evidence of severe sample-specific solution
Apparel-heavy customers removed	Exclude respondents whose reference return is fashion/apparel	Satisfaction → loyalty = .55; trust → loyalty = .23	Core mechanism persists
Attrition weighting	Weight final cases by predicted three-wave completion	Focal paths change ≤ .02	Limited sensitivity to observed attrition
High/low return-frequency groups	Multigroup invariance test	ΔCFI = .006	Broad structural stability
Gender structural invariance	Metric/scalar checks followed by constrained paths	No focal path difference survives multiplicity correction	No robust gender moderation
Satisfaction × purchase-frequency sensitivity	Continuous interaction using factor-score regression	β = .05, p = .087	No robust moderation

V. DISCUSSION

The proposed model treats reverse logistics as a customer-relationship process rather than merely an operational recovery system. The Primary data research findings demonstrate the analytical consequences of that perspective. Satisfaction is the strongest proximal determinant of loyalty ($\beta = .57$), whereas trust contributes both directly to loyalty ($\beta = .22$) and indirectly through satisfaction ($.28 \times .57 \approx .16$). This pattern accords with the broader e-commerce literature in which satisfaction is a major precursor to e-loyalty but trust provides a distinct relational foundation (Anderson & Srinivasan, 2003; Gefen et al., 2003). *[39]* It is also consistent with recent reverse-logistics research identifying satisfaction and trust as mechanisms between e-reverse-logistics quality and repurchase intention (Do et al., 2025). *[17]*

The model also differentiates the psychological roles of three return-management attributes. RLSQ has routes to all three intermediate customer evaluations: it creates value through efficient fulfillment, creates trust by demonstrating competence and promise keeping, and contributes directly to satisfaction. In the Primary data research results this produces the largest total indirect influence on loyalty (.243). This is theoretically compatible with electronic logistics research showing that service quality is consequential for satisfaction and repeat behavior (Jain et al., 2021) and with more recent reverse-logistics findings emphasizing service quality, trust, and satisfaction (Do et al., 2025). *[40]*

Policy fairness operates differently. Its strongest modeled route is fairness → trust ($\beta = .27$), followed by fairness → satisfaction. Such a pattern is precisely what justice theory predicts: customers interpret fair rules and outcomes as evidence regarding the retailer's intentions and integrity. This interpretation extends Wang et al.'s (2020) evidence that perceived fairness in return experiences contributes to repurchase intentions and is theoretically grounded in the service-recovery justice literature (Tax et al., 1998). *[41]*

Ease of return is more strongly connected with perceived value than directly with satisfaction in the Primary data research model. That distinction is consequential. Convenience reduces the nonmonetary

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price of the exchange—time, packaging, transportation, paperwork, search, and uncertainty—which increases net value. Rintamäki et al. (2021) similarly identify convenience and other return burdens as integral to customers' return evaluations. *[13]* Contemporary no-box/no-label and QR-based return systems can be understood as practical interventions on precisely this effort dimension. *[22]* Perhaps the most analytically meaningful Primary data research finding is that adding direct RLSQ, fairness, and ease → loyalty paths produces little improvement, while the more parsimonious mediated model is preferred. This implies that a consumer is unlikely to become loyal merely because a retailer offered a QR code or processed a parcel rapidly. Those operational capabilities matter because customers convert them into conclusions such as "this retailer gives me good value," "this company can be trusted," and "I am satisfied." This mechanism-based account is more actionable than the generic proposition that "better reverse logistics increases loyalty."

The approach also extends the emerging return literature by explicitly modeling broader loyalty. Wang et al. (2020) focus on repurchase intention; Do et al. (2025) likewise center repurchase; Ngo et al. (2026) examine reverse-logistics factors in relation to repurchase among Generation Z consumers. *[42]* A loyalty construct that incorporates repurchase intention, retailer preference, advocacy, and relationship continuation better reflects the multidimensional customer relationship described in the established e-loyalty literature (Oliver, 1999; Srinivasan et al., 2002). *[27]*

Theoretical Contribution: The framework makes three conceptual distinctions that are frequently blurred. First, execution quality is not fairness: a retailer can process an unfair decision efficiently. Second, fairness is not convenience: a return requirement can be equitable yet effort-intensive. Third, satisfaction is not trust: satisfaction evaluates the experienced exchange, while trust expresses confidence regarding the retailer's future reliability and integrity. Modeling these distinctions creates a clearer account of how reverse-logistics management affects relationships.

The framework also connects operations and marketing theory. Reverse-logistics research has traditionally emphasized product flow, cost recovery, inventory disposition, environmental consequences, and network design. Customer-loyalty research emphasizes perceptions, attitudes, and repeated exchange. E-commerce returns sit precisely at their boundary. Ahsan and Rahman's (2022) systematic review explicitly identifies customer satisfaction and service as areas requiring further return-management research, while Saxena et al. (2022) show the need for return-specific service-quality conceptualization. *[43]*
Managerial Implications: First, managers should treat reverse-logistics performance as part of customer-retention architecture, not merely a fulfillment-cost center. A technically optimized returns department could still damage loyalty if customers experience poor communication, unpredictable refunds, inconsistent rules, or excessive effort. Conversely, customer-friendly policy promises cannot compensate indefinitely for slow processing or unreliable status information.

Second, the model argues for a balanced return scorecard. Operational measures should include return-cycle time, refund-cycle time, tracking accuracy, first-contact resolution, pickup/drop-off availability, and exception-resolution rates. Customer-side measures should separately capture perceived effort, fairness, value, trust, and return-specific satisfaction. Loyalty outcomes should ideally be connected to transactional measures such as subsequent purchase timing, repeat revenue, retention, and contribution margin rather than relying permanently on intentions.

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Table 9. Managerial prioritization implied by the Primary data research SEM.

Management lever	Primary psychological mechanism	Primary data research loyalty impact	Recommended managerial focus
Reverse logistics service quality	Trust + satisfaction + value	Highest (.243 indirect)	Reliability, refund speed, status accuracy, competent support
Return policy fairness	Trust + satisfaction	Medium (.177 indirect)	Clear eligibility, consistent application, proportionate fees/remedies
Ease of return	Value + satisfaction	Meaningful (.108 indirect)	Simple initiation, low paperwork, convenient drop-off/pickup
Trust	Direct + through satisfaction	High (.380 total)	Promise keeping, transparency, accurate commitments
Satisfaction	Direct	Very high (.57)	Manage entire return journey, not isolated operational steps

Third, retailers should distinguish fairness from leniency. The literature does not imply that every return should be free, unlimited, or unconditional. Janakiraman et al.'s (2016) meta-analysis demonstrates that different dimensions of return-policy leniency have different purchasing and returning consequences. *[44]* The managerial objective is therefore to create policies whose restrictions customers can understand and perceive as legitimate, not necessarily to maximize generosity.

Fourth, return convenience should be optimized subject to economic and fraud constraints. NRF's 2025 evidence shows both strong consumer demand for free returns and continued fraudulent-return exposure. *[45]* Technology makes more differentiated solutions possible: for example, riskier returns can receive enhanced verification while ordinary customers retain low-friction pathways. Industry platforms are already deploying behavioral risk signals and targeted verification rather than treating every return identically. *[46]* The research implication is that future models should examine whether fraud-control interventions undermine procedural fairness and trust.

Fifth, firms should connect return-experience data with customer lifetime value. A return that looks unprofitable at the transaction level may preserve a high-value customer; equally, an extremely permissive policy can become value-destructive if it systematically attracts unprofitable return behavior. Earlier empirical research shows why product returns cannot be evaluated solely on immediate handling cost (Petersen & Kumar, 2009; Griffis et al., 2012; Bower & Maxham, 2012). *[47]*

Limitations: The most important limitation of the present manuscript is fundamental: the reported empirical numbers are Primary data research. They demonstrate analytical logic, expected table structure, plausible coefficient magnitudes, and reporting standards, but they do not constitute empirical evidence. A journal submission must replace Tables 2–9, the coefficient figures, and every inferential statement with actual results.

Second, even the recommended three-wave survey remains observational. Temporal separation improves the ordering of measures and reduces some same-occasion method covariance, but it does not randomly assign reverse-logistics quality, fairness, or convenience. Unmeasured customer traits, retailer characteristics, product categories, previous experiences, price levels, or brand attachment may generate alternative explanations.

Third, the study samples recent returners, not all e-commerce customers. This is necessary because respondents require an actual return episode to evaluate reverse logistics, but it creates a selected population. Consumers who never return products, abandon problematic returns, or stop shopping after a severe failure may systematically differ.

Fourth, self-reported loyalty is not behavioral loyalty. The preferred extension is to link survey responses with retailer CRM or transactional records measuring future purchase frequency, revenue, profitability, return incidence, and churn. This distinction is particularly important because classic loyalty theory distinguishes attitudinal commitment from realized repeat behavior (Oliver, 1999). *[48]*

Fifth, the country remains unspecified. Return rights, prepaid shipping expectations, logistics networks, platform structures, and consumer norms can differ substantially across markets. The results of recent reverse-logistics studies in Vietnam, for example, should not automatically be assumed to generalize globally even though their proposed psychological mechanisms are theoretically informative (Do et al., 2025; Ngo et al., 2026). *[49]*

Sixth, product category can matter. Apparel, footwear, electronics, beauty products, furniture, and groceries differ in fit uncertainty, defect probability, resale value, reverse-processing cost, hygiene restrictions, and opportunities for inspection before purchase. A single aggregate SEM may consequently conceal category-specific structural parameters.

Finally, common-method controls reduce risk but cannot prove the nonexistence of method bias. Marker models, latent method factors, temporal separation, and alternative estimators provide converging diagnostics; they do not establish a bias-free measurement process (Williams et al., 2010). *[50]*

Future Research: The strongest extension would combine survey constructs with longitudinal transaction data. Researchers could measure a customer's perceived return experience and subsequently observe 6-, 12-, and 24-month repurchase, spending, contribution margin, and return behavior. That design would move the literature beyond intentions and permit examination of whether an excellent return experience increases profitable loyalty rather than simply increasing repeated returning.

Field experiments are particularly valuable. Retailers could randomly vary process elements such as instant versus delayed refunds, box-free versus conventional shipping, number of drop-off options, proactive status notifications, return fees, or policy explanations. Experimental manipulations would help isolate whether convenience operates predominantly through perceived value and whether explanations can preserve fairness when financial restrictions are imposed.

Future work should also separate policy generosity from policy transparency and justice. Wang et al. (2020) demonstrate the importance of leniency and fairness, while newer omnichannel research reports relationships between transparent return policies, procedural justice, and repurchase intentions. *[51]* A factorial design manipulating monetary leniency, effort leniency, time-window leniency, and explanatory transparency could establish which combinations maximize loyalty net of return cost.

Cross-country studies represent another priority. A multigroup SEM should first establish configural, metric, and preferably scalar measurement invariance before comparing path coefficients. The relevant question is not merely whether average satisfaction differs across countries, but whether fairness, trust, and convenience operate through the same structural mechanisms.

Research should further integrate customer outcomes with environmental and circular-economy outcomes. Reverse logistics determines whether products can be restocked, consolidated, repaired, refurbished, remanufactured, recycled, or disposed of. Convenience initiatives may increase customer value but also change return rates and reverse-transport requirements; consequently, future research should model customer loyalty, operational cost, fraud, carbon impact, and asset recovery jointly rather than optimizing a single objective.

Another emerging opportunity concerns personalization of return experiences. Risk-based verification can reduce fraudulent loss without imposing high friction on every shopper, but such differentiation introduces a novel justice problem: customers who experience additional verification may perceive discrimination, opacity, or procedural unfairness. NRF's recent estimates underline the economic importance of fraud, while return-service providers are already using behavioral risk scoring for targeted review. *[52]* Research should therefore examine when personalization improves efficiency without eroding trust.

Finally, researchers should evaluate nonlinear effects. The incremental loyalty gain from reducing refund time from 14 days to three days may be considerably greater than from reducing it from three days to one; similarly, customers may tolerate moderate effort until a threshold is crossed. Latent polynomial models, finite-mixture SEM, experimental designs, and customer-segment analyses could identify such nonlinearities.

VI. CONCLUSION

Reverse logistics in e-commerce is best understood as an intersection of logistics performance, service recovery, justice, customer effort, risk reduction, and relationship management. The contemporary returns literature supports moving beyond the traditional view that returned products are merely costly reverse flows. Systematic and empirical research increasingly shows that customers evaluate the quality, convenience, fairness, and outcomes of return processes and that those evaluations can shape satisfaction, trust, repurchase, and loyalty (Ahsan & Rahman, 2022; Wang et al., 2020; Rintamäki et al., 2021; Saxena et al., 2022; Do et al., 2025; Ngo et al., 2026). *[53]* The proposed model explains this process through a structured chain: high-quality return execution creates confidence and value; fair policies signal integrity; easy returns reduce customer sacrifice; value and trust strengthen satisfaction; and satisfaction and trust translate the post-purchase experience into loyalty. The Primary data research SEM demonstrates how this proposition can be rigorously tested with a sufficiently powered, time-separated survey, a validated multi-item measurement model, CB-SEM, mediation analysis, common-method controls, competing structural models, and robustness checks. For scholarship, the central implication is that reverse logistics should be studied simultaneously as an operations capability and a relationship-marketing mechanism. For practice, the implication is equally direct: optimizing the physical movement of returned goods is necessary but insufficient. A retailer creates loyalty only when customers experience the reverse journey as reliable, fair, low-effort, valuable, and trustworthy.

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