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Analysis on Revenue Leakage Detection in E-Commerce in Navi Mumbai: A Data-Driven Approach to Identifying Hidden Sources of Business Loss.

[1]Dr Siji Nambiar, [2]Mr Amaan Shaikh, [3]Mr Debasish Behera

[1]Assistant Professor, D. Y. Patil Deemed to be University, School of Humanities & Sciences, Belapur, Maharashtra, India.

[23]Students, Department of MCA, D. Y. Patil Deemed to be University, School of Humanities & Sciences, Belapur, Maharashtra, India.

Abstract - *Online retailers lose revenue through returns, refunds, order cancellations, payment failures, delivery costs and deep discounting, yet these sources of leakage are usually monitored separately. This study examines how young online shoppers perceive the main drivers of revenue leakage and whether they believe that analyzing order history, discounts, returns, refunds and cancellations can identify orders at higher risk of financial loss. A survey-based approach was used. A nine-item online questionnaire was completed by 103 respondents (94% aged 18–25) between 23 and 28 October 2026. Five test cases, each with a null and an alternative hypothesis, were examined using exact binomial tests, a chi-square goodness-of-fit test and Fisher's exact test at the 5% significance level. Size or fit problems were the most frequent reason for returns (37.5%), although not significantly more frequent than the other reasons ($p = 0.1037$), and order cancellations were the most frequently cited source of financial loss (31.3%). Most respondents (81.3%, 95% CI 64.7–91.1) agreed that order-history analysis can identify higher-risk orders ($p < 0.001$), the only null hypothesis rejected. The sample is small, homogeneous and self-selected, so the findings are indicative and motivate analysis of real order-level transaction data.*

Keywords - Revenue Leakage, E-Commerce, Product Returns, Discounts, Order Cancellations, Business Intelligence, Exploratory Survey, Hypothesis Testing

INTRODUCTION

Online shopping has changed how businesses earn revenue and, at the same time, how they lose it. Revenue leakage refers to income that a business should have earned but loses between the moment an order is placed and the moment it is finally settled. Typical sources are returned goods, refunds, cancelled orders, failed payments, delivery costs absorbed by the seller and discounts deeper than needed to win the sale. Each source sits in a different system (order management, payments, logistics, marketing), so their combined effect on profit is easy to underestimate.

The scale of returns alone is large. Patel et al. [1], citing a 2021 National Retail Federation study, report that USD 218 billion of purchases were returned from US online retail sales of USD 1.05 trillion, and cite an estimate that returning a USD 50 product cost roughly USD 33 once customer care, transport, processing and liquidation are counted. If similar proportions hold for refunds, cancellations and discount-led sales, a retailer that tracks only headline revenue will miss much of where margin disappears.

Commercial tools now market "revenue leakage" dashboards that combine refunds, discount abuse and payment failures [2], [3], but the consumer behavior behind these events is rarely studied together. This study takes a first, exploratory step from the customer side. It surveys 103 young online shoppers about their discount behavior, return reasons, perceived sources of loss and views on business intelligence (BI) monitoring.

The study also tests five hypotheses, each framed with a null and an alternative hypothesis, to show which of its findings can be distinguished from chance in a sample of this size. The findings are intended to guide a larger analysis using real order-level data.

PROBLEM STATEMENT

Most online retailers can tell how much they sold last month; far fewer can say how much of that revenue was later given back through cancellations, refunds, returns and discounts, or which orders were most likely to be given back. When these events are reported in separate systems, a business may treat each as an acceptable cost of trading, even though together they can erode margin substantially. Customers, meanwhile, generate these events through their own choices: whether to chase a discount, whether to keep or return an item, and whether to complete or cancel an order. Understanding how customers see these behaviors is a useful first step toward monitoring them.

Significance. The study contributes in three ways.

First, it brings returns, refunds, cancellations, discounts and payment failures into one frame, rather than treating returns alone. Second, it records what young online shoppers believe about the usefulness of order-history analytics, which indicates whether customer-facing and seller-facing tools built around risk scoring are likely to be accepted. Third, it states openly which of its results can and cannot be separated from chance with 103 respondents, which is information that later, larger studies can use to plan sample sizes.

Scope and organization. The study is limited to self-reported perceptions from a small convenience sample, and it does not measure actual losses. The paper first reviews related work and sets out a conceptual framework of leakage components. It then states the objectives and the null and alternative hypotheses, describes the method, reports the results and test cases, interprets them, discusses implications for retailers, and closes with limitations, future work and a conclusion.

LITERATURE REVIEW

Returns and the role of fit

Digital Commerce 360 [4], reporting a global Narvar survey of 3,519 consumers aged 19 to 65, found that wrong size, fit or color was the top reason for returns, cited by 46% of those returning to non-Amazon retailers and 34% for Amazon returns. The same report notes that 48% of US consumers "bracket" their purchases by ordering several versions in order to return some, and that 13% of US

consumers said they would not shop with a retailer again because of their last returns experience. A separate survey of 1,052 consumers mentioned in the report found size to be the top reason for 55% of respondents. These figures come from trade-press reporting of industry surveys, so they are indicative rather than definitive. They also show that a return has a second cost beyond logistics: it can reduce future sales.

Patel et al. (2022) [1] provide the most detailed peer-reviewed evidence found for this study. They analyzed 496,365 items ordered by 75,707 customers of a Swedish fashion e-commerce platform between 2015 and 2022, in which about 37.5% of items were returned. They describe poor fit as the main reason for online fashion returns and report that customers who used a size-recommendation tool, which was used for about 7.3% of items, were 0.65% more likely to return an item. At the same time, quarterly customer value rose for repeat customers who used the tool. The authors also compared several machine-learning models for predicting returns; the best model reached an AUC of roughly 0.7, and the strongest predictors were total order value, gross margin, category and price, while use of the size tool ranked among the least important. For revenue leakage, two points matter. Returns can be partly predicted from order attributes available at the time of sale, which supports order-level risk scoring. And a feature that slightly raises returns may still pay for itself through loyalty, so returns should not be judged in isolation.

Patel et al. (2022) [1] also summaries earlier work. They cite Hong and Pavlou (2014) for the finding that fit uncertainty raises online returns more than quality uncertainty, cite industry estimates that return rates in online fashion apparel range from 25% to 40% overall and can reach 75% for some categories, and report commentary that a retailer's best customers often have the highest return rates. They also stress that item-level and order-level return costs are hard to estimate, and in their own calculation they assume returns cost about 10% of the average item price. This difficulty in costing returns is itself a form of leakage risk: what is not measured cannot be managed.

Return policies and the purchase–return trade-off

Return policies are a deliberate lever. Janakiraman, Syrdal and Freling (2023) [5] reviewed the return-policy literature in a meta-analysis that classifies leniency

along five dimensions: money, time, effort, scope and exchange. As summarised in published coverage of the study, lenient policies increase purchases but also produce a smaller, still significant rise in returns. The dimensions behave differently: monetary and effort leniency are associated with more purchases, while time and exchange leniency are associated with fewer returns. One explanation offered in that coverage is the endowment effect, whereby the longer a customer keeps a product the more attached to it they become and the less likely they are to return it. Petersen and Kumar [6] examined perceived risk and product returns in a field experiment, and coverage of related work notes that a satisfactory return experience was associated with lower perceived risk. For a leakage framework the implication is that returns cannot simply be minimised: part of their cost buys additional sales, and monitoring should help separate productive from unproductive returns.

Discounts and purchase behaviour

Discounts reliably change purchase behaviour, and part of that effect goes beyond the price saving. Bayer and Ke(2023) [7] used a sequential-search experiment and found that when subjects did not know in advance which shops offered discounts, the probability of

purchase rose by 19 percentage points in discounting shops, even after controlling for the benefit of the discount and for risk preferences; when discounts were known in advance, the bias was much smaller (7 percentage points) and only weakly significant. They interpret this as a discount bias. Sheehan et al. [8] show that a discount's magnitude becomes more predictive of purchase intention later in an online shopping trip, which suggests that placing shallow discounts early may improve the effectiveness of a retailer's discount portfolio. Roy et al. [9] studied price expectations in an online store experiment and found that, at constant cost, deep short discounts (for example 15% in the first week) lifted sales more than shallow long ones (3% for five weeks), mainly among an "outside-looking" class of shoppers who compare prices with other stores. Together these studies show that discount design affects who buys and when, and that a discount can lift sales while lowering margin. They do not, however, follow discount-led purchases through to later returns or refunds, which is where leakage would show.

Monitoring tools and the research gap

On the practice side, a commercial Shopify application describes leakage as a bundle of cart abandonment, checkout drop-off, refunds, discount abuse and payment failures, with a real-time dashboard, a leakage score and recovery recommendations [2]. A fraud-prevention vendor describes a dashboard that helps merchants identify items that sell at a loss and shipping methods prone to fraud [3]. These sources show that the idea of a "leakage score" is already being marketed, but they are product descriptions rather than evaluations, and they do not report how well such scores identify high-risk orders.

Synthesis and gap. Taken together, the literature shows that returns are large, partly predictable and linked to fit [1], [4]; that return policies trade sales against returns [5], [6]; and that discounts shift behaviour [7]–[9]. What the searches conducted for this paper did not locate is peer-reviewed work that jointly models discounts, returns, refunds and cancellations at order level to score loss risk, or that asks shoppers whether such analytics seem credible. This study addresses the second part, from the customer side, and prepares the ground for the first.

Conceptual Framework

To make the questionnaire items comparable, the study uses a simple framework in which gross order revenue is reduced by six leakage components, each of which can be attached to an individual order (Fig. 1). Table 1 defines the components and gives an example of a metric a retailer could compute for each. The framework is a working structure proposed for this study, not an established standard.

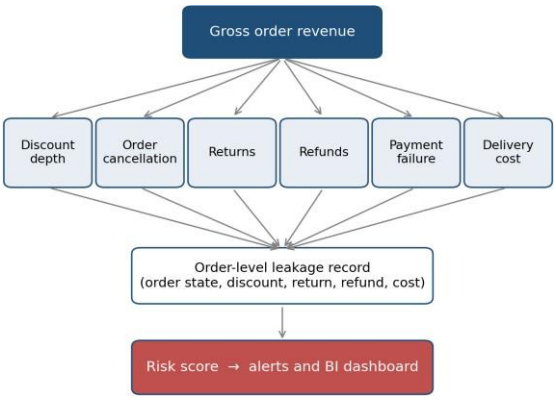

Fig. 1. Conceptual framework of order-level revenue leakage.

Table 1. Leakage components and example metrics

Component	Definition	Example metric
Discount depth	Price reduction given relative to list price	Discount ÷ list price, per order
Order cancellation	Order cancelled before it is delivered	Cancelled ÷ placed orders
Returns	Goods sent back after delivery	Returned ÷ delivered orders (units or value)
Refunds	Money repaid to the customer, with or without a return	Refund value ÷ net order value
Payment failure	Payment that fails, is reversed or is charged back	Failed or reversed ÷ attempted payments
Delivery cost	Shipping, handling and reverse-logistics cost absorbed by the seller	Absorbed cost ÷ order value

A retailer could combine these into a single leakage rate for an order, defined as the share of gross order value that is not retained as realised revenue after discounts, cancellations, refunds, payment losses and absorbed delivery costs. Because each component depends on the order's state (delivered, cancelled, returned, refunded or failed), the framework treats the order state as the natural unit for assigning loss, and

the risk score in Fig. 1 as an estimate of the probability and size of loss for an order before it settles. The five questionnaire themes map onto the framework as follows: discount items correspond to discount depth, the return-reason item to returns, the loss-factor item to all six components, and the last two items to the risk score and its presentation in a BI tool.

Illustration (hypothetical). Suppose an order has a list value of 1,000 currency units and a 20% discount (200), so the customer pays 800. A damaged item later leads to a partial refund of 300, and the seller absorbs 60 in delivery cost. Realised revenue is 800

− 300 − 60 = 440, and the leakage rate is (1,000 −

440) ÷ 1,000 = 56%, made up of 20 points from the discount, 30 from the refund and 6 from delivery. The numbers are invented to show the arithmetic and are not drawn from the survey. Because a discount is

an intentional price concession, a retailer may prefer to report it separately from unplanned leakage such as refunds and failed payments.

Objectives of the Study

1. To examine how discounts influence the purchasing decisions of young online shoppers.
2. To identify the most common reasons for returning online products.
3. To identify the factors respondents perceive as the largest contributors to financial loss in e-commerce.
4. To examine whether respondents believe that order-history analysis can identify high-risk orders.
5. To identify the BI features respondents consider most useful for monitoring revenue leakage.

Research Hypotheses

Each hypothesis is tested as a separate test case with a null hypothesis (H_0) and an alternative hypothesis (H_1), where π denotes a population proportion. All tests are two-sided at $\alpha = 0.05$.

1: Discounts and Contribution Margin

- $H0_1$ (Null Hypothesis): There is no significant relationship between discount levels and contribution margins in e-commerce transactions.
- $H1_1$ (Alternative Hypothesis): Higher discount levels are significantly associated with lower contribution margins in e-commerce transactions.

2: Returns, Refunds, and Cancellations

- $H0_2$: There is no significant relationship between returns, refunds, cancellations, and estimated revenue leakage.
- $H1_2$: Higher rates of returns, refunds, and cancellations are significantly associated with greater estimated revenue leakage.

3: Revenue Leakage Across Product Categories

- $H0_3$: There is no significant difference in estimated revenue leakage across product categories.
- $H1_3$: Estimated revenue leakage differs significantly across product categories.

4: Operational Costs and Revenue Leakage

- $H0_4$: Operational costs, including shipping and return-processing costs, have no significant relationship with estimated revenue leakage.
- $H1_4$: Higher operational costs are significantly associated with greater estimated revenue leakage.

5: Predictive Detection of Revenue Leakage

- $H0_5$: Historical transaction data cannot significantly predict transactions with a high risk of revenue leakage.
- $H1_5$: Historical transaction data can significantly predict transactions with a high risk of revenue leakage.

6: Payment Discrepancies and Revenue Leakage

- $H0_6$: There is no significant relationship between payment discrepancies and estimated revenue leakage.
- $H1_6$: Payment discrepancies are significantly associated with estimated revenue leakage.

Table 2. Test cases and decision rules

ID	Variables	Statistical test	Decision rule
TC1	Agreement item (agree/strongly agree vs neutral)	Exact binomial test against π = 0.50	Reject H01 if p < 0.05

TC2	Bought mainly for a high discount (yes/no)	Exact binomial test against $\pi = 0.50$	Reject H_{02} if $p < 0.05$
TC3	Return reason (4 categories, n = 31 returners)	Chi-square goodness of fit (df = 3)	Reject H_{03} if $p < 0.05$
TC4	Discount influence × discount-driven purchase (2×2)	Fisher's exact test	Reject H_{04} if $p < 0.05$
TC5	Main loss factor (post-sale event vs other)	Exact binomial test against $\pi = 0.50$	Reject H_{05} if $p < 0.05$

RESEARCH METHODOLOGY

Research Design

The study used a descriptive, survey-based design to examine how young online shoppers perceive the sources of revenue leakage and the usefulness of BI monitoring.

Sample Size

A total of 103 respondents participated. A convenience sample was obtained by circulating the questionnaire link. Responses were received between 2026-10-23 and 2026-10-28, with 24 of them on the first day, which indicates a single circulation network.

Data Collection

Primary data were collected through a structured Google Forms questionnaire of closed-ended items on age group, shopping frequency, discount influence, discount-driven purchasing, return reasons, perceived loss factors, price as a profit signal, preferred BI features and agreement that order-history analysis can identify high-risk orders (Appendix A). The exported dataset numbers its items 1, 2 and 4–10; item 3 is absent and is not analysed.

Variables Studied

The study considered the respondents' age group and shopping frequency; how often discounts influence their purchases and whether they have bought mainly for a discount; their most common reason for returning a product; the factor they believe contributes most to financial loss; whether they think price alone indicates seller profitability; and which BI feature they consider most useful.

Data Analysis

The data were analysed using frequencies, percentages and 95% Wilson confidence intervals. The five test cases in Table 2 were run in Python (SciPy). Fisher's exact test was chosen for TC4 because expected cell counts fell below five. The results were interpreted at a 5% significance level (α

$= 0.05$), without correction for multiple testing. Because two respondents were under 18, TC1 and TC2 were repeated without them. A supplementary Fisher's exact test and several cross-tabulations were also run for exploratory purposes and are labelled as such.

Instrument and Measurement

All items were closed-ended. Shopping frequency, discount influence and agreement were measured on ordered categories (for example never, rarely, sometimes, often, always), while return reason, loss factor and BI feature were single-choice nominal items. Because each construct was measured by a single item, internal-consistency statistics such as Cronbach's alpha do not apply, and results should be read item by item. No pilot test was recorded for the instrument.

Data Quality Checks

The exported dataset was checked for missing values and duplicate responses. There were 0 missing values and 0 responses with identical answers to every item, so all 103 responses were retained.

Timestamps were used only to describe the collection window. "All of the above" was treated as a separate category for the BI-feature item and was not redistributed among the other options.

Ethical Considerations

No names or other direct identifiers were analysed. Participation was voluntary and based on a circulated link. Two respondents reported being under 18, so the analysis for the two majority tests was repeated without them, and the authors should confirm that parental or institutional consent requirements were satisfied before publication. [Insert ethics approval or informed-consent statement.]

Sensitivity of the Tests

With n = 103, an exact two-sided binomial test against

0.50 at $\alpha = 0.05$ requires at least 23 of 103 respondents

(71.9%) on one side to reject the null hypothesis. A result of 22 of 103 (68.8%) gives p = 0.050 and does not reach this threshold, while 23 of 103 would (p = 0.020). The tests therefore detect only large departures from an even split, and a non-significant result here means that the data are inconclusive, not that the null hypothesis is true.

RESULTS AND ANALYSIS

4.1 Demographic Profile

A total of 103 respondents participated in the study. The largest group was 18–25 years, consisting of 30 respondents (93.8%); the remaining 2 (6.2%) were below 18. Most respondents shop online at least monthly (22 of 103, 68.8%): daily 3, weekly 8,

monthly 11, occasionally 7 and rarely 3.

4.2 Discounts and Purchasing

Discounts influence purchases “sometimes” for 14 respondents (43.8%), “often” for 11 (34.4%) and “always” for 5 (15.6%); only two said “never” or “rarely”. Twenty-two respondents (68.8%) said they had bought a product mainly because of a high discount.

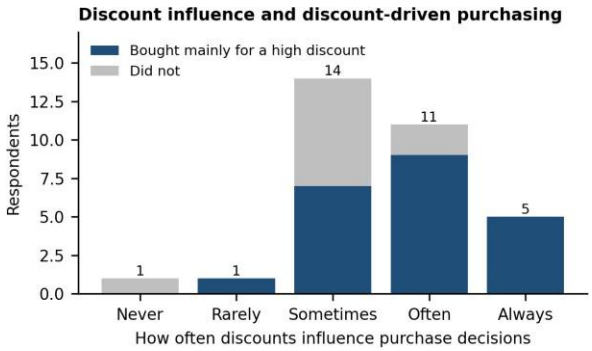

Fig. 2. Discount influence and discount-driven purchasing.

4.3 Reasons for Returns

Size or fit issues were the most common reason for returns (12, 37.5%), followed by wrong or damaged product (7, 21.9%), poor quality (7, 21.9%) and product not as described (5, 15.6%). One respondent had never returned a product.

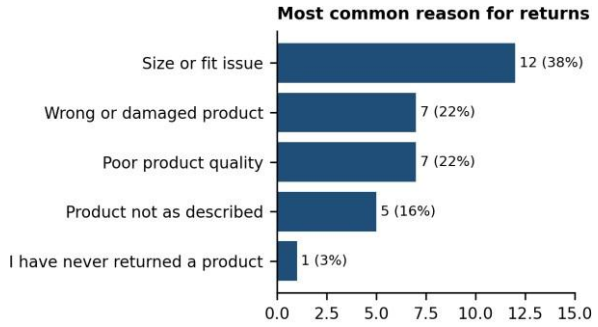

Fig. 3. Most common reason for returning an online product.

4.4 Perceived Sources of Financial Loss

Order cancellations were most often named as the largest contributor to financial loss (10, 31.3%), ahead of product returns (7, 21.9%), refunds (5, 15.6%), excessive discounts (5, 15.6%), delivery costs (4, 12.5%) and payment issues (1, 3.1%).

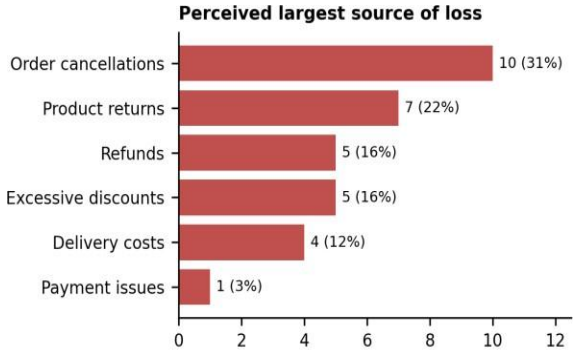

Fig. 4. Factor perceived to contribute most to financial loss.

4.5 Price as a Signal of Profitability

Asked whether selling price alone indicates how profitable a product is for the seller, 13 respondents (40.6%) were not sure, 10 (31.3%) said yes and 9 (28.1%) said no. Few respondents therefore reject the idea that price reveals profit, and many are uncertain.

4.6 Order-History Analysis and Risk

Fourteen respondents agreed (43.8%) and twelve strongly agreed (37.5%) that analysing order history, discounts, returns, refunds and cancellations can identify higher-risk orders; six were neutral (18.8%) and none disagreed. Overall 26 of 103 (81.3%) agreed.

4.7 Preferred BI Features

Real-time sales and profit dashboards were most often chosen (10, 31.3%), followed by "all of the above" (9, 28.1%), returns and refund tracking (6,

18.8%) and discount and pricing analysis (5, 15.6%). Product-level profit reports and high-risk order alerts were each chosen once.

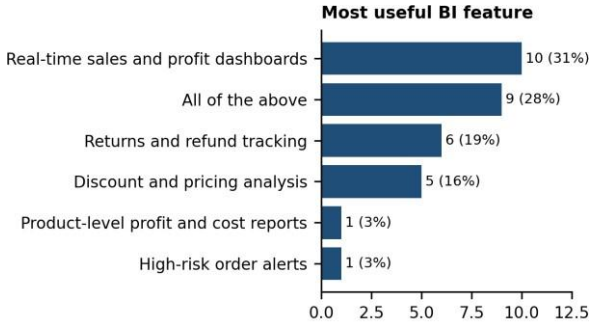

Fig. 5. BI feature judged most useful.

4.8 Respondent Subgroups and Cross-Tabulations

The following comparisons are exploratory and are not part of the five test cases. Respondents who shop online daily or weekly (n = 11) were slightly more likely to report discount-driven buying than those who shop monthly or less (n = 21): 72.7% against 66.7%. Fisher's exact test gave p = 1.000, so there is no evidence of a difference. All three daily shoppers had bought mainly for a discount, but with so few respondents per frequency group (Fig. 6) the pattern cannot be interpreted further.



Fig. 6. Discount-driven buying by shopping frequency (counts shown above bars).

Perceived loss factors were grouped as returns or refunds (n = 12), cancellations (n = 10), excessive discounts (n = 5) and delivery or payment (n = 5) and compared with the preferred BI feature. Among the 12 respondents who named returns or refunds as the main loss, only 2 chose returns and refund tracking as the most useful BI feature, whereas 7 chose real-time dashboards. Among the 5 who named excessive discounts, only 1 chose discount and pricing analysis. Respondents therefore did not generally pick the specialised tool that matched the loss they considered largest; they favoured general dashboards or "all of the above".

Agreement with the order-history statement was similar across views on price as a profit signal. Strong agreement was given by 3 of 10 respondents who thought price indicates profit, 4 of 9 who did not, and 5 of 13 who were unsure. Among those who bought mainly for a discount, 4 of 22 named excessive discounts as the main loss factor, compared with 1 of 10 of those who had not. These counts are too small to support any inference.

4.9 Confidence Intervals for Key Proportions

Table 3. Key proportions with 95% Wilson intervals (n = 103)

Result	k	Share	95% CI
Shops online at least monthly	22	68.8%	51.4–103%
Discounts often/always matter	16	50.0%	33.6–66.4%
Size or fit is main return reason	12	37.5%	22.9–54.7%
Cancellations are main loss	10	31.3%	18–48.6%
Not sure price shows profit	13	40.6%	25.5–57.7%
Strongly agree: order-history analysis	12	37.5%	22.9–54.7%
Dashboards are most useful BI feature	10	31.3%	18–48.6%
Dashboards or "all of the above"	19	59.4%	42.3–74.5%

The intervals are wide. For example, the share naming size or fit as the main return reason could plausibly lie anywhere between about 23% and 55%, and the shares naming cancellations and dashboards between 18%

and 49%. Rankings between categories with similar counts, such as the 12 respondents citing size or fit and the 7 citing wrong or damaged products, should therefore be treated as tentative.

4.10 Hypothesis Test Summary

Table 4. Results of the test cases

Case	Test Result	Estimate	p-value	Decision
TC1	Binomial vs 0.50	26/103 = 81.3% (95% CI 64.7–91.1)	< 0.001	**Significant**; reject H_{01}
TC2	Binomial vs 0.50	22/103 = 68.8% (95% CI 51.4–103)	= 0.050	Not significant; retain H_{02}
TC3	$\chi^2(3) = 3.45$	12, 7, 7, 5 (expected 7.75)	= 0.1037	Not significant; retain H_{03}
TC4	Fisher's exact	87.5% vs 50%; OR = 7.0	= 0.054	Not significant; retain H_{04}
TC5	Binomial vs 0.50	22/103 = 68.8% (95% CI 51.4–103)	= 0.050	Not significant; retain H_{05}

Interpretation

The hypotheses were tested using the questionnaire responses of 103 participants. Because the data are categorical and the sample is small, exact tests were used where possible and the chi-square test was applied only where all expected counts were at least five. The significance level was set at 5%.

Hypothesis 1: Order-History Analytics

The exact binomial test gave $p < 0.001$. Since $p < 0.05$, H_{01} was rejected in favour of H_{11}. A significant majority of respondents agreed that order-history analysis can identify higher-risk orders. The 95% interval (64.7–91.1%) stays above 50%. Without the two respondents under 18 the result is unchanged (24 of 30, $p = 0.001$).

Hypothesis 2: Discount-Driven Purchasing

The proportion who bought mainly because of a discount was 68.8% ($p = 0.050$). Since p is not below 0.05, H_{02} was retained, although the result sits at the edge of significance. Without the two respondents under 18 it becomes 21 of 30 ($p = 0.043$), so the conclusion depends on one or two respondents and should be treated as unstable.

Hypothesis 3: Reasons for Returns

The chi-square goodness-of-fit test gave $\chi^2(3) = 3.45$, $p = 0.1037$. Since $p > 0.05$, H_{03} was retained. Size or fit was the most frequent reason, but the data do not show that it is cited significantly more often than the other reasons in this sample.

Hypothesis 4: Discount Sensitivity

Among the 16 respondents for whom discounts often or always matter, 14 (87.5%) had bought mainly for a discount, against 8 of 16 (50%) of the others. Fisher's exact test gave $p = 0.054$, so H_{04} was retained. The direction matches the prediction, but the evidence is not significant at the 5% level.

Hypothesis 5: Perceived Source of Loss

22 of 103 respondents (68.8%) named order cancellations, returns or refunds as the largest source of loss ($p = 0.050$). Since p is not below 0.05, H_{05} was retained, although the result is again at the boundary.

Robustness

Three checks bear on how far the results can be trusted. First, removing the two respondents under 18 leaves the only rejected null hypothesis (TC1) rejected, and moves TC2 from $p = 0.050$ to $p = 0.043$, which shows that the borderline results are fragile in both directions. Second, the choice of test matters for TC4: a chi-square test would have been unreliable because most expected counts were below five, so Fisher's exact test was used, and it gave $p = 0.054$. Third, the binomial tests detect only large departures from an even split, as noted in the methodology, so the four retained null hypotheses should be read as inconclusive rather than as evidence of no effect.

Overall Interpretation

Only one of the five null hypotheses was rejected: respondents overwhelmingly believe that order-history analysis can identify risky orders. Results for discount-driven purchasing, discount sensitivity and post-sale loss point in the expected direction but are not significant at this sample size. These results describe perceptions and should not be read as proof of actual loss behaviour.

Discussion Returns and fit

Size or fit was the most frequent return reason (37.5%), which agrees in direction with the industry survey in [4] and the academic evidence in [1]. The chi-square test, however, could not show that it is cited more often than the other three reasons, and its interval (about 23% to 55%) overlaps with theirs. Taken with [1], where fit-related returns are common but a size tool changed returns only slightly, the practical lesson is that fit is a persistent source of returns that is not removed by any single feature. A retailer should therefore track fit-related returns by product and size and treat the fix as an information problem, as well as a logistics one.

Cancellations as a visible loss

Order cancellations (31.3%) were named more often than returns (21.9%) as the biggest source of financial loss, even though the academic literature reviewed here concentrates on returns. One possible reason is visibility: cancellations are experienced directly by the shopper, whereas the cost of a return is borne out of sight by the seller. Another is that shoppers may regard a cancellation as a wasted sale and a return as a normal part of buying. The present data cannot distinguish between these explanations, but they suggest that a leakage framework should record cancellations explicitly, ideally separated into those made before dispatch and those made after.

Discounts and purchase behaviour

About two-thirds of respondents (68.8%) reported having bought mainly because of a high discount, and those for whom discounts often or always matter reported discount-driven buying at 87.5% compared with 50.0% for the rest. Both results point in the direction predicted by [7]–[9], but neither is significant at the 5% level, and the majority result depends on one or two respondents. Shopping

frequency did not separate discount-driven buyers from others. The evidence is therefore consistent with a discount effect without confirming it. For leakage monitoring, the important question that the literature leaves open is what happens to discount-led orders afterwards, for example whether they are returned or refunded more often, and this needs order-level data.

Analytics, dashboards and alerts

Agreement that order-history analysis can identify high-risk orders was the study's one significant result, and its interval stays well above 50%. This is encouraging for risk-scoring tools. Two cautions apply. First, the item is a leading statement with a one-sided scale, so acquiescence bias probably inflates agreement. Second, respondents did not choose alert-type tools: 59.4% preferred dashboards or "all of the above" and only one respondent chose high-risk order alerts as the most useful feature. Respondents also did not tend to choose the tool that matched their own view of the largest loss. This is consistent with a preference for broad visibility over a single score, or with limited familiarity with alerting tools. In either case, a staged design, with a dashboard first and alerts layered on top, seems better matched to what respondents say they want.

Price as a poor guide to profit

Only 28.1% of respondents rejected the idea that selling price alone shows how profitable a product is for the seller, and 40.6% were unsure. Shoppers appear to have little insight into margins, discounts and the costs of returns. This matters for sellers because it implies that discount-driven buyers cannot be expected to moderate their own behaviour, and that margin protection has to come from the seller's side, through discount design, return policy and monitoring.

Comparison with prior literature

Table 5 sets the main results beside the evidence reviewed earlier. The comparisons show consistency of direction, but the measures differ (self-reported perceptions here, observed behaviour or industry surveys elsewhere), so they are not like-for-like tests.

Table 5. Main results compared with prior evidence

Theme	This study	Prior evidence
Fit and returns	Size or fit was the most cited return reason (37.5%) but not significantly above the others	Size, fit or colour was the top reason in an industry survey (46% non-Amazon, 34% Amazon) [4]; fit is the main reason for fashion returns [1]
Discounts	68.8% bought mainly for a discount ($p = 0.050$)	Unannounced discounts raised purchase probability by 19 points in an experiment [7]
Cancellations	Named as the largest loss by 31.3%	The reviewed literature concentrates on returns [1], [4]–[6]
Analytics	81.3% agree that order history can flag risky orders	Order attributes predict returns with an AUC of roughly 0.7 [1], which supports plausibility but not accuracy

Return policy	Not measured	Lenient policies raise purchases and returns [5]

Implications for retailers

Four implications follow, each tentative given the sample. First, leakage should be measured as a combined, order-level quantity rather than as separate returns, refund and cancellation reports. Second, since [1] shows that order value, margin, category and price carry predictive information about returns, a first risk score can be built from fields most retailers already hold. Third, because return policies trade sales against returns [5], any attempt to cut returns should be tested against effects on purchases and repeat business [1], [4]. Fourth, discount design deserves monitoring in its own right, since depth and timing influence who buys [7]–[9].

RECOMMENDATIONS

1. Record order state precisely (delivered, cancelled before dispatch, cancelled after dispatch, returned, refunded, payment failed) so that loss can be assigned to a cause.
2. Track fit-related returns by product and size and improve size guidance where they are concentrated, while not expecting a size tool alone to remove them [1].
3. Report cancellations as a separate leakage line, not as a subset of returns or refunds.
4. Link discount depth to downstream return and refund rates for the same orders, to see whether deep discounts bring unprofitable demand.
5. Start with a dashboard that shows the combined leakage rate by category, then add risk alerts once their accuracy has been checked on historical orders.
6. Estimate the full cost of a return, including handling and liquidation, rather than using a flat assumption [1].

Objectives revisited

1. **Discounts.** Thirty of 103 respondents (93.8%) said discounts influence their purchases at least sometimes, and 68.8% had bought mainly because of a high discount, although the majority test was only borderline.
2. **Return reasons.** Size or fit led (37.5%), followed by wrong or damaged product and poor quality (21.9% each) and product not as described (15.6%), but the differences between reasons were not significant.
3. **Loss factors.** Order cancellations were named most often (31.3%), then returns (21.9%), refunds and excessive discounts (15.6% each), delivery costs (12.5%) and payment issues (3.1%).
4. **Order-history analysis.** A significant majority (81.3%) agreed that it can identify higher-risk orders.
5. **BI features.** Real-time dashboards (31.3%) and "all of the above" (28.1%) were preferred; specialised alerts were rarely chosen.

Key Findings

1. **Young shoppers formed the sample.** Ninety-four per cent of respondents were aged 18–25, so the results mainly reflect young, frequent online shoppers.
2. **Discounts matter to most respondents.** Thirty of 103 said discounts influence their purchases at least sometimes, and 68.8% had bought mainly because of a high discount, although the majority test was at the edge of significance.
3. **Size and fit lead return reasons.** Size or fit was the most common reason (37.5%), consistent with industry and academic evidence [1], [4], but it was not significantly more frequent than the others.
4. **Cancellations are seen as the largest loss.** Order cancellations (31.3%) were named more often than returns (21.9%), suggesting leakage frameworks should not focus on returns alone.
5. **Price does not reveal profit to most respondents.** Only 28.1% rejected the idea that price alone shows profitability, and 40.6% were unsure.
6. **Strong belief in order-history analytics.** 81.3% agreed that order-history analysis can identify high-risk orders; this was the one significant result.
7. **Preference for broad visibility.** Dashboards and "all of the above" were preferred (59.4% together), while only one respondent chose high-risk order alerts as the most useful feature.
8. **Shopping frequency did not separate discount-driven buyers.** Discount-driven buying was reported by 72.7% of daily or weekly shoppers and 66.7% of others ($p = 1.000$), so frequency of shopping alone does not explain it.
9. **Preferred tools did not match perceived loss.** Of 12 respondents naming returns or refunds as the main loss, only 2 chose returns and refund tracking as the most useful BI feature; most chose general dashboards.
10. **Results are exploratory.** Several results sit at $p \approx 0.05$ and depend on one or two respondents, so they should be confirmed with a larger sample.

Limitations of the Study

1. **Small and homogeneous sample.** The study has 103 respondents, 94% aged 18–25, recruited

through one network. The results cannot be generalised to online shoppers at large, and the confidence intervals are wide.

2. **Perceptions, not behaviour.** All data are self-reported. The study has no order, refund or loss figures, so it cannot estimate leakage rates by order state, and respondents' beliefs about loss may differ from what retailers actually experience.
3. **Instrument.** Item 3 is missing from the export, the agreement item is a leading statement whose responses ran only from neutral to strongly agree (likely acquiescence bias), single-item measures cannot be tested for reliability, no pilot test was recorded, and several response categories contain a single response.
4. **Statistical power.** With n = 103, only large departures from an even split can be detected (at least 23 of 103). Five test cases were run without multiplicity correction, and two borderline results (p = 0.050) depend on one or two respondents.
5. **Respondents under 18.** Two respondents were minors; ethics and consent requirements should be confirmed, and results are reported with and without them.
6. **Self-selection and timing.** Most responses arrived on the first day of collection through one network, so respondents may share similar habits and views, and responses reflect a single point in time.
7. **Literature.** The review is targeted rather than systematic, and some sources are industry reports, vendor descriptions or secondary summaries of academic work.

Future Scope of Study

The natural next step is empirical analysis of real order-level data from one or more retailers. Using the framework in Fig. 1, each leakage component would be defined for every order, loss rates would be estimated by order state, and a risk score built from order history would be tested on whether it predicts net-margin loss on orders held out from model fitting. Table 6 lists the fields such a dataset would need. These are proposed fields only; no such data were collected in this study.

Table 6. Proposed fields for an order-level leakage dataset

Field	Description
order_id, order_date	Unique order key and date placed
customer_id	Pseudonymised customer key, for repeat behaviour
order_state	Delivered, cancelled (before or after dispatch), returned, refunded, payment failed
category, quantity	Product category and units ordered
list_price, discount	Price before discount and discount amount
payment_method	Payment type, including cash on delivery if used
delivery_cost	Delivery and handling cost absorbed by the seller
return_reason	Reason code for returns and cancellations
refund_amount	Money repaid, with timing
net_margin	Margin after all of the above

Analysis could then proceed in stages: describe leakage by order state; model the probability of cancellation, return and refund from order attributes; combine these into an expected-loss score; and compare the score with realised loss. A larger and more diverse follow-up survey, with a balanced agreement scale, a complete item set and enough respondents to detect moderate effects, would strengthen the consumer-side evidence. Studies could also compare product categories, platforms and payment methods separately, and test whether design changes such as clearer size guidance or discount limits reduce measured leakage.

CONCLUSION

This exploratory study examined how young online shoppers perceive the drivers of revenue leakage. Respondents link returns mainly to fit problems, name order cancellations as the largest source of loss, frequently buy because of discounts and, in a statistically significant majority, believe that order-history analysis can identify risky orders. The other four test cases did not reach significance at this sample size. The findings support monitoring that combines discounts, returns, refunds, cancellations and payment failures at the level of the individual order, and they motivate testing that idea on real transaction data.

Three messages stand out for practice. Leakage is best seen as a combined, order-level quantity, with order state as the unit that links each loss to a cause. Cancellations deserve a place beside returns and refunds in any monitoring scheme. And because

respondents favour broad dashboards over single alerts, a staged introduction of analytics, starting with visibility and adding risk scoring once it has been validated on historical orders, is likely to be better

received. These conclusions remain provisional until they are tested on real order data and on a larger and more varied sample.

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Note. Hong and Pavlou (2014) is mentioned as reported in [1] and was not consulted directly. Volume and page details for [5] come from the reference list of [1], and its findings follow published summaries; verify both against the originals.