Synergy of Consumer Purchasing Behavior Analysis and Return Reason Categorization in Reducing Product Return Rates: A Study at IKEA Indonesia Fulfillment Center

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Abstract

The rise of e-commerce has led to a notable escalation in product return rates, presenting a substantial difficulty in the administration of fulfillment centers. This study is to examine the impact of consumer purchasing behavior analysis and the classification of product return causes on return rates at IKEA Indonesia fulfillment centers. A quantitative methodology was employed by gathering data via a questionnaire administered to 150 respondents who had engaged in purchases and product returns within the past six months. Data analysis was performed with SmartPLS by evaluating the measurement model (outer model) and the structural model (inner model). The findings indicated that both independent variables have a positive and significant influence on product return rates. The path coefficient for Consumer Purchasing Behavior Analysis (X1) is 0.574 (T-Statistics 13.299; P-Values 0.000), whereas the path coefficient for Product Return Reason Categorization (X2) is 0.456 (T-Statistics 10.989; P-Values 0.000). Both variables concurrently account for 92.7% of the variance in product return rates (R-Square 0.927), indicating a model with exceptionally robust predictive capability. This discovery underscores the significance of an integrative strategy that combines the analysis of customer behavior patterns with the categorization of product return causes in developing data-driven return management strategies. This study offers theoretical advancements in the supply chain management literature, particularly regarding reverse logistics and consumer behavior analytics, alongside practical implications for IKEA Indonesia in formulating policies aimed at decreasing product return rates by enhancing the accuracy of product information, quality control, and logistics processes.

1. Introduction

The advancement of digital technology has induced substantial transformations in the worldwide economic environment, especially within the e-commerce industry, which has experienced swift expansion in recent years. This expansion is marked by rising online transaction volumes, evolving customer behavior, and a transition in the distribution process from conventional models to fulfillment center-based systems. During this shift, product returns have emerged as a significant concern for numerous retail organizations, including IKEA Indonesia, which manages fulfillment centers to facilitate product distribution to customers.

In e-commerce, product returns have evolved from a mere ancillary task to a vital component influencing supply chain efficacy and customer contentment. Frequent product returns by consumers not only elevate operational burdens and logistics expenses but may also diminish views of service quality and brand dependability. In the context of IKEA Indonesia, a high return rate might adversely affect fulfillment center productivity, encompassing reprocessing, re-storage, and administrative reconciliation, thereby depleting resources. Consequently, handling product returns necessitates a more strategic approach, encompassing both operational considerations and a profound comprehension of consumer behavior.

Numerous prior research have investigated the primary factors contributing to product returns, such as damaged items, product discrepancies, unsatisfactory quality, or delayed delivery (Feng et al., 2019; Li et al., 2019; Öztürk & DÜNDAR, 2020). Nonetheless, the majority of these research have concentrated exclusively on logistics or product quality in isolation, and few have methodically combined consumer purchasing behavior aspects with the causes for product returns. Understanding client purchasing patterns, including purchase frequency, product variety, average transaction value, and return history, can serve as significant markers for anticipating return inclinations.

This research gap arises from the absence of a comprehensive approach that concurrently analyzes the correlation between consumer purchasing behavior and the classification of product return causes. Most prior research has concentrated on a singular facet, either from the logistics management viewpoint or the customer standpoint, without amalgamating the two into a comprehensive analytical framework. Comprehending the motivations of consumers who often return products will greatly aid companies in developing more suitable, effective, and data-informed return policies.

This study aims to address the question: "How can the synergy between consumer purchasing behavior analysis and return reason categorization mitigate product return rates at IKEA Indonesia fulfillment centers?"

This study aims to examine and analyze several variables of consumer purchasing behavior that may impact the elevated product return rate at IKEA Indonesia fulfillment centers. The analyzed behavioral indicators encompass buy frequency, average transaction value, product variety acquired, interval between transactions, and prior return history. This study seeks to systematically identify and classify reasons for product returns into several primary categories, including damaged or defective items, non-conforming specifications, inaccurate product descriptions, subpar quality, and delayed delivery that fails to meet anticipated expectations.

This study seeks to analyze the concurrent and partial effects of purchase behavior and return reasons on consumer return tendencies. This method is anticipated to yield a more thorough comprehension of return patterns, facilitating the formulation of more focused operational strategies. This study aims to furnish data-driven advice to fulfillment center management for developing more effective product return policies, enhancing logistics efficiency, service accuracy, and overall customer experience. This research aims to connect consumer behavior analysis with the effectiveness of return logistics systems in contemporary fulfillment centers.

This research is innovative due to its integrative methodology, merging two primary dimensions: purchasing behavior and return reasons, to examine product return challenges within fulfillment center operations. This research is both exploratory and useful, employing real data from IKEA Indonesia's operations as a case study.

This methodology has not been extensively employed in prior research, especially within the Indonesian setting, and is anticipated to yield both scientific and practical benefits. This research theoretically enhances the literature on supply chain management, specifically with reverse logistics and customer behavior analytics. Moreover, the methodology employed corresponds with the trend of leveraging data analytics for operational decision-making in e-commerce and omnichannel enterprises. The findings of this research are anticipated to aid IKEA Indonesia in formulating evidence-based policies to minimize return logistics expenses, enhance service precision, and sustain customer loyalty by improving the shopping experience.

Fulfillment centers serve as essential distribution hubs linking inventory, packing, and shipping systems to final consumers. Increased return volumes, if unaddressed, lead to the overburdening of fulfillment centers, so interrupting the primary distribution channel. Consequently, identifying customers with a strong likelihood of returning and comprehending their motivations for returns are essential for formulating proactive strategies, including modifying product information, enhancing consumer education, and reassessing complaint management procedures.

This research presents dual contributions: firstly, enhancing consumer behavior theory and logistics management through a comprehensive, data-driven methodology; secondly, offering strategic recommendations for companies to optimize fulfillment center operational efficiency while ensuring a favorable customer experience. The results of this study are anticipated to underpin the development of more flexible, efficient, and customer-centric operational strategies, particularly in the progressively competitive landscape of digital logistics.

1.1 Analysis of Consumer Purchasing Behavior on Product Return Rates

The analysis of consumer purchasing behavior encompasses the identification and assessment of customer interaction patterns throughout the transaction process, including purchase frequency, average transaction value (AOV), time intervals between transactions (recency), diversity of products acquired, and historical return behavior. A comprehensive grasp of these characteristics is essential in contemporary fulfillment centers, since it facilitates predictive decision-making to reduce product returns.

Makov et al. (2023) assert that elevated purchase frequency is intricately linked to customer loyalty and product familiarity, hence mitigating the likelihood of dissatisfaction and return behaviors. The average transaction value indicates customer prudence in product selection, as posited by Tüylü and Eroğlu (2022), who noted that customers with elevated AOV are generally more meticulous in their purchase decisions.

Zheng et al. (2024) stated that recency indicates the degree of consumer engagement. Consumers who engage in purchasing typically possess more pragmatic expectations and a more profound brand experience, resulting in a reduced likelihood of returns. Adebayo (2022) demonstrated that significant fluctuation in purchased product categories indicates exploratory behavior, which is susceptible to product mismatches and results in returns. The historical return data is a significant predictor of future return behavior (Ritola et al., 2020).

Understanding this purchase behavior is essential for formulating data-driven tactics to identify high-risk client segments for product returns. Strategies include enhanced product education, refined online catalog information, and client risk profiling can be formulated by analyzing these behavioral indicators.

Hypothesis 1 (H1): Analysis of consumer purchasing behavior significantly influences product return rates at IKEA Indonesia fulfillment centers.

1.2 Categorization of Product Return Reasons and Return Rates

The categorization of return reasons is a methodical technique to classifying the diverse motivations that compel consumers to return things. This classification of reasons is essential for pinpointing deficiencies that can be enhanced within the supply chain and customer service in fulfillment center operations.

Feng et al. (2019) asserted that defective or malfunctioning products are the principal cause of returns, directly linked to production and quality control issues. Li et al. (2019) shown that deviations from customer

expectations—particularly regarding size, color, and specifications—constitute a significant factor, especially for intangible objects like furniture, which are challenging to assess online.

Öztürk and DÜNDAR (2020) asserted that imprecise product descriptions exacerbate the disparity between client expectations and reality, resulting in unhappiness that influences returns. Moreover, Abdulla et al. (2019) emphasized the significance of logistical elements, such as shipment delays, which adversely affect customer experience and promote returns, particularly when the product is required by a set deadline.

By recognizing and categorizing the causes of product returns, organizations can formulate more targeted policies. Enhancing the precision of product descriptions, reassessing logistics vendor efficacy, and augmenting quality control prior to shipment. Ultimately, this can diminish return rates and enhance consumer satisfaction.

Hypothesis 2 (H2): Categorization of product return reasons has a significant impact on product return rates at IKEA Indonesia fulfillment centers.

1.3 Synergy between Consumer Purchasing Behavior and Return Reasons on Return Rates

While the aforementioned factors have been examined independently in the literature, the amalgamation of purchasing behavior and return cause categorization within a unified analytical framework remains uncommon. A comprehensive understanding of both enhances forecasting accuracy in minimizing overall product return rates.

Numerous research indicate that integrating a behavioral approach with return reasons might produce a more precise identification of high-risk consumer segments (Ritola et al., 2020; Tüylü & Eroğlu, 2022). By employing analytical models that integrate these two dimensions, organizations can formulate data-driven strategies such as customer segmentation, intelligent order processing, and product recommendation systems customized to consumer attributes.

1.4 Research Model

The conceptual model in this study is built on the theory and results of previous studies described. This model visualizes the relationship between two independent variables:

X1: Consumer Buying Behavior Analysis

X2: Product Return Reason Categorization

Both variables are assumed to influence Y: Product Return Rate, either partially or simultaneously.

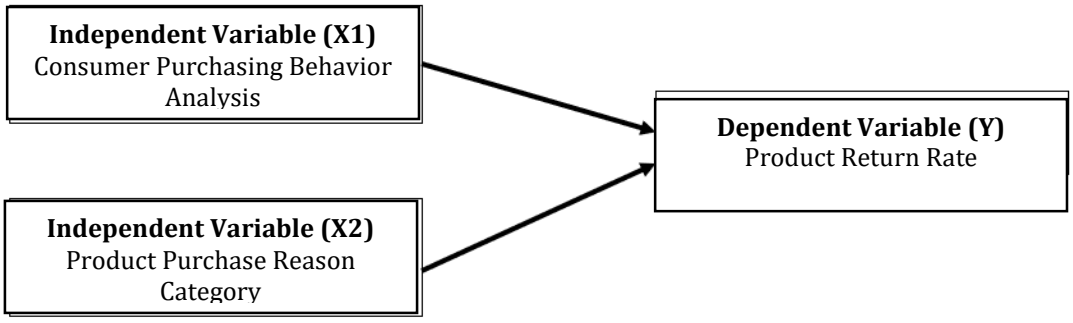

Fig 1. Research Model

2. Research Methods

2.1 Research Design

This study utilizes a quantitative explanatory approach, sometimes referred to as causal or verification research, which seeks to elucidate the causal relationship between independent and dependent variables grounded in theoretical frameworks and prior research findings. This methodology is suitable since it may empirically test hypotheses and elucidate the relationships among two or more variables through quantitative data analysis.

The employed study strategy is cross-sectional, indicating that data collecting occurs at a singular moment in time. This design is pertinent as the study employs historical data from product return transactions at IKEA Indonesia fulfillment centers during the last six months. This design facilitates the examination of the relationship between the researched variables without requiring prolonged continuous observation.

2.2 Data Sources and Sampling Techniques

This study employs primary data collected directly from customers of IKEA Indonesia via an online questionnaire. This primary data collection aims to investigate consumer experiences, behaviors, and perceptions related to the product purchase and return procedure in the context of IKEA Indonesia's e-commerce services. The utilization of primary data enables researchers to more extensively capture aspects of consumer behavior, particularly those inadequately represented by transaction data within the company's internal system.

The questionnaire employed in this study was meticulously crafted based on indicators of the research variables: analysis of consumer purchasing behavior (X_1), categorization of causes for product returns (X_2), and product return rates (Y). The questionnaire was thereafter disseminated to individuals who fulfilled specific requirements. The employed sample approach was purposive sampling, a non-probability method that depends on particular considerations and criteria for picking respondents. The study's inclusion criteria comprised IKEA Indonesia consumers who had engaged in online purchases and had experience with product returns within the preceding six months. Moreover, only participants who thoroughly and consistently completed the questionnaire were incorporated into the study.

Purposive sampling was considered suitable as it enabled researchers to gather data from groups pertinent to the study's topic. The intended number of respondents in this study was established to satisfy the minimum criteria for statistical analysis, specifically for multiple linear regression testing. Prior to additional data analysis, a validation and preliminary assessment will be performed to ascertain the quality of the data utilized, including the evaluation of response completeness and the coherence of the questionnaire's logic. This methodology is anticipated to yield precise and representative data to tackle the study challenge and aims.

2.3 Operational Definitions and Research Instruments

To guarantee measurement precision and interpretative clarity, each variable in this study is operationally defined and assessed using indicators that have been theoretically and empirically validated. This study employed a questionnaire as the principal data collection tool, utilizing closed-ended statements on a five-point Likert scale, ranging from strongly disagree to strongly agree.

The initial independent variable is the examination of consumer purchasing behavior (X_1), operationally defined as the patterns and trends of customers acquiring products via the IKEA e-commerce platform. This variable is assessed using five primary indicators: purchase frequency during a designated timeframe, average transaction value (AOV), the interval between purchases (recency), the diversity of product categories acquired by customers, and their product return history. These indications delineate the intensity, consistency, and exploratory inclinations of buyers about the given products.

The second independent variable is the classification of product return reasons (X_2), which operationally denotes customers' principal motivations for returning purchased items. Measurements were executed according to five prevalent categories of issues in e-commerce: defective or damaged items, discrepancies

between products and their descriptions or expectations (including size, color, or features), diminished product quality, erroneous product descriptions, and delayed delivery beyond the promised timeframe. Each area was organized as statements to ascertain client perceptions and experiences concerning these factors.

The dependent variable in this study was the product return rate (Y), operationally defined as the probability of customers returning things post-purchase. This variable was assessed based on the frequency of customer returns during the past six months and their opinion of the probability of future returns. This variable indicates the degree of customer dissatisfaction with a product or service and serves as a measure of the efficacy of returns management executed by the fulfillment center.

The study tool was an online questionnaire developed with a focus on content validity and contextual pertinence. Prior to extensive implementation, the questionnaire underwent validation and reliability testing using restricted trials and Cronbach's Alpha assessments. The gathered data was subsequently coded and analyzed utilizing SmartPLS statistical software to facilitate the hypothesis testing procedure and the previously established conceptual model.

2.4 Data Analysis Techniques

The data analysis in this study was executed methodically and in phases to address the research objectives and evaluate the established hypotheses. The analysis commenced with descriptive statistics to elucidate the features of each variable, both independent and dependent. Descriptive statistics were employed to compute measures of central tendency, including the mean, measures of dispersion, such as the standard deviation, and the maximum and minimum values for each indicator in the questionnaire. This stage is essential for comprehending the initial data distribution and identifying potential outliers.

Subsequently, classical assumptions were evaluated as a prerequisite for employing multiple linear regression analysis. A normality test was performed to verify that the distribution of residual data adhered to a normal distribution. A multicollinearity test was employed to identify significant correlations between independent variables (X_1 and X_2), which may compromise the regression outcomes. A heteroscedasticity test was performed to assess the constancy of residual variance (homoscedasticity) as a validation of the regression model's stability.

Upon satisfying all fundamental regression assumptions, the subsequent step is to do multiple linear regression analysis. This method assesses the degree to which the independent factors, Consumer Purchasing Behavior Analysis (X_1) and Product Return Reason Categorization (X_2), affect the dependent variable, Product Return Rate (Y), both collectively and individually. The F-test assesses the collective impact of independent variables on the dependent variable, whereas the t-test evaluates the individual contribution of each independent variable.

Furthermore, the analysis is enhanced by computing the coefficient of determination (R^2) to assess the degree to which differences in X_1 and X_2 account for variations in Y. A high R^2 score signifies that the model possesses strong prediction capability for the phenomenon being examined. The comprehensive statistical analysis will be performed utilizing the newest version of SPSS software or SmartPLS 4, according to the distribution and attributes of the questionnaire data. This approach aims to yield precise and dependable insights that facilitate strategic, data-informed decision-making.

3. Result and Discussion

3.1 Respondent Demographics

This study involved 150 respondents, IKEA Indonesia customers who had made online purchases and returned products within the past six months. Based on demographic data, the majority of respondents were female, indicating that IKEA Indonesia's online market segment is dominated by female consumers who tend to be more active in online transactions. Most respondents were in the 20–30 age range, followed by those in the 31–

40 age group. This reflects that the productive age group is the primary user of IKEA's online shopping service. In terms of shopping frequency, respondents who had made two to three purchases in the past six months dominated the study sample, followed by respondents who had purchased more than three times. This data indicates a tendency towards repeat shopping behavior on IKEA's online platform. Nearly all respondents had returned a product at least once, indicating that returns in e-commerce are a common occurrence, even on the platform of a globally renowned company like IKEA. Complete information on the distribution of respondents is presented in Table 1 for gender, Table 2 for age, and Table 3 for shopping frequency, which helps understand the characteristics of the study population.

Table 1. Gender

Gender	Amount	Percentage
Male	60	40%
Female	90	60%

Source: Artha Nugraha Jonar., 2025

Table 2. Age

Age Range	Amount	Percentage
20-30 years old	80	53,3%
31-40 years old	50	33,3%
>40 years old	20	13,4%

Source: Artha Nugraha Jonar., 2025

Table 3. Shopping Frequency

Frequency	Amount	Percentage
1 time	30	20%
2-3 times	90	60%
>3 times	30	20%

Source: Artha Nugraha Jonar., 2025

3.2 Measurement Model Results (Outer Model)

The measurement model test (outer model) seeks to verify the validity and reliability of the research instrument. The analysis results demonstrate that all indicators within the three research constructs possess outer loading values over 0.7, signifying that each indicator substantially contributes to the representation of its latent construct. The Average Variance Extracted (AVE) for the Consumer Buying Behavior Analysis (X1) is 0.743, for the Categorization of Product Return Reasons (X2) is 0.533, and for the Product Return Rate (Y) is 0.771. Hair et al. (2021) assert that an AVE value exceeding 0.5 signifies satisfactory convergent validity; hence, all variables in this study fulfill the criteria for convergent validity. The Composite Reliability (CR) values for X1, X2, and Y were 0.935, 0.851, and 0.944, respectively, and the Cronbach's Alpha for all three constructions above 0.7. This signifies that the research instrument has exceptional internal consistency. The results of the outer model test validate that the instrument employed in this study is suitable and dependable for assessing the constructs examined.

Table 4. Outer Model Results

Variable	AVE	Composite Reliability	Cronbach's Alpha
Consumer Purchasing Behavior Analysis (X1)	0.743	0.935	0.913x`
Categorization of Product Return Reasons (X2)	0.533	0.851	0.78
Product Return Rate (Y)	0.771	0.944	0.926

Source: Artha Nugraha Jonar, 2025

3.3 Structural Model Results (Inner Model)

The inner model test was performed to assess the strength of the links among the latent variables in the research model. The research revealed an R-Square (R^2) value of 0.927 for the Product Return Rate (Y) variable, indicating that 92.7 percent of the variance in the product return rate is attributable to the Consumer Buying Behavior research (X1) and Product Return Reason Categorization (X2) variables. The residual 7.3 percent was affected by extraneous factors, like the company's return policy, the quality of after-sales service, and external logistics considerations. Chin (1998) posits that a R^2 value exceeding 0.67 is classified as a very strong model; thus, this study model has exceptional predictive capability. The results demonstrate that both independent variables considerably contribute to elucidating the product return rate.

Table 5. Inner Model

Relation	Path Coefficient
X1 → Y (Consumer Purchasing Behavior Analysis → Product Return Rate)	0.574
X2 → Y (Product Return Reason Categorization → Product Return Rate)	0.456

Source: Artha Nugraha Jonar., 2025

3.3 Bootstrapping Results (Hypothesis Testing)

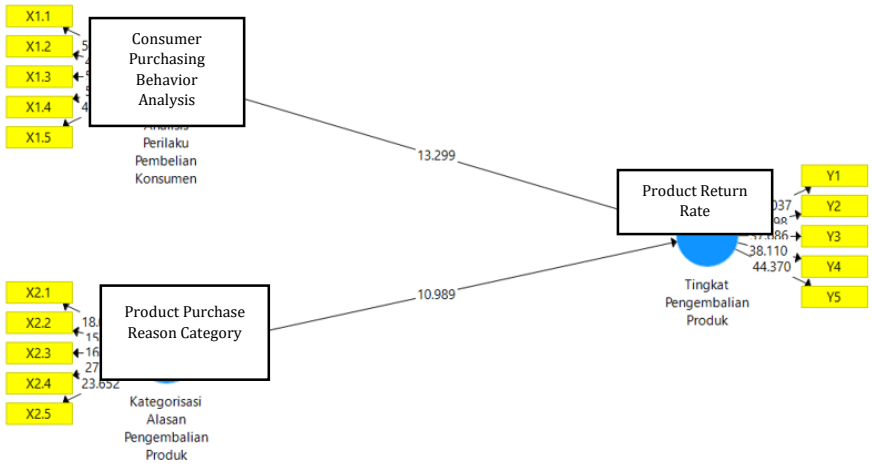

Fig 2. Bootstrapping Model

Table 6. Bootstrapping Results

	T Statistics	P Values
X1 → Y (Consumer Purchasing Behavior Analysis → Product Return Rate)	13.299	0.000
X2 → Y (Product Return Reason Categorization → Product Return Rate)	10.989	0.000

Source: Artha Nugraha Jonar., 2025

3.4 Discussion

This study elucidates the elements affecting product return rates at IKEA Indonesia's fulfillment centers. The substantial and notable influence of Consumer Buying Behavior Analysis on Product Return Rates suggests that regular shoppers with elevated transaction values generally possess heightened expectations for service and product quality. This corresponds with the findings of Makov et al. (2023), indicating that consumers who shop frequently are more discerning in evaluating product appropriateness, hence increasing the likelihood of product returns when expectations are unmet. These findings corroborate Adebayo's (2022) assertion that consumers exhibiting exploratory shopping behavior are more susceptible to discontent. In the context of IKEA, these findings underscore the necessity of delivering precise and transparent product information along with consumer education to mitigate misaligned expectations.

The classification of product return reasons significantly affects product return rates. These findings correspond with the studies conducted by Feng et al. (2019) and Li et al. (2019), which highlighted defective products, non-compliant specs, and erroneous product descriptions as primary contributors to product returns. The findings at IKEA Indonesia's fulfillment facility underscore the necessity of establishing an integrated return reason classification system to enable systematic analysis of return trends. This will allow the organization to implement more focused remedial measures, like optimizing packing procedures, augmenting pre-shipment inspections, and reassessing logistics partners to mitigate delivery delays.

The exceptionally high R-Square value signifies that integrating consumer purchasing behavior analysis with product return reason categorization is a suitable method for comprehending the dynamics of product return rates. This corresponds with the perspective of Ritola et al. (2020), who asserted that a cohesive comprehension of these two elements can establish the foundation for data-driven policymaking. For IKEA Indonesia, these findings offer a scientific foundation for formulating more proactive and adaptive return management strategies, including offering product recommendations tailored to customer shopping preferences, implementing educational initiatives on product utilization, and delivering timely consultation services in cases of product discrepancies.

Hypothesis testing was performed via bootstrapping by analyzing the T-statistics and P-values. The research indicated that the initial hypothesis (H1), concerning the impact of Consumer Purchasing Behavior research on Product Return Rates, was validated with a T-statistic of 13.299 and a P-value of 0.000. This signifies that consumer purchasing behavior exerts a favorable and substantial impact on product return rates. The second hypothesis (H2), concerning the impact of Product Return Reason Categorization on Product Return Rates, was accepted, exhibiting a T-statistic of 10.989 and a P-value of 0.000. The findings indicate that the clarity and structure of reasons for product returns significantly enhance the probability of consumer returns. Both independent factors concurrently exert a strong impact on product return rates, as demonstrated by the elevated R-square value in the structural model.

4. Conclusions

This study finds that the analysis of consumer purchasing behavior and the categorization of product return reasons significantly and positively influence product return rates at IKEA Indonesia fulfillment centers, both individually and collectively. Analysis of customer purchasing behavior reveals that increased shopping frequency correlates with elevated average transaction values, whereas a broader product variety purchased enhances the probability of product returns. This is directly associated with the rising consumer expectations for the appropriateness of products and services. The classification of causes for product returns, such as product quality, specification inconsistencies, erroneous product descriptions, and delayed delivery, emerged as the primary factors affecting return decisions. These two variables concurrently accounted for 92.7% of the variance in product return rates (R-Square 0.927), hence demonstrating substantial predictive efficacy for this study model. The results underscore the significance of a comprehensive approach that combines consumer behavior analysis with the classification of product return reasons to formulate data-driven return management policies that are more responsive to the dynamics of e-commerce.

This study advises IKEA Indonesia to enhance the precision of product descriptions on its online platform to mitigate disparities in customer expectations. Moreover, enhanced quality control is essential prior to shipment, particularly for product categories exhibiting elevated return rates. Organizations are encouraged to consistently use a data-driven return reason classification system to swiftly discern product return trends, facilitating targeted preventive and corrective measures. Enhancing coordination with logistics partners is essential to guarantee timely delivery, as delays significantly influence return decisions.

Further research is advised to incorporate moderating or mediating variables such as customer pleasure, customer loyalty, or after-sales service quality for a more thorough understanding. The study population may be extended to encompass additional e-commerce firms with analogous traits, facilitating a wider applicability of the findings. Longitudinal study is essential to observe fluctuations in product return rates over an extended duration, facilitating a more comprehensive investigation of return trends and patterns.

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