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Research paper

The Role of AI in Preventing Return Fraud: A Study of Amazon's Flexible Return Policy and Consumer Behavior

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Abstract

Purpose – The purpose of this study is to examine the role of Artificial Intelligence (AI) in identifying and preventing return fraud on Amazon. It also seeks to explore the behavioral patterns and motivations behind the exploitation of Amazon's flexible return policy by consumers.
Design/Methodology/Approach – This research employed a quantitative approach using structured online surveys distributed to Amazon customers with return experience. The data were analyzed using descriptive statistics, chi-square tests, and regression analysis. Reliability was tested through Cronbach's Alpha to ensure consistency of constructs such as AI awareness, policy perception, and return behavior.
Findings – The study found that higher awareness of AI monitoring significantly reduces the likelihood of return fraud. Demographic factors such as age and shopping frequency were also found to influence return behavior. Perceptions of policy leniency increased the chances of policy exploitation. Overall, AI was viewed positively when implemented with transparency and fairness.
Originality/Value – This study contributes to the emerging body of literature on AI applications in fraud prevention within e-commerce, particularly in return management. It provides actionable insights for online retailers, especially Amazon, on leveraging AI ethically to enhance fraud detection while maintaining customer trust and satisfaction.

Keywords: *Artificial Intelligence; Return Fraud; Amazon; Consumer Behavior; Flexible Return Policy; E-commerce.*

1. Introduction

Amazon has transformed the online shopping paradigm through its customer-centric approach, notably with its widely known flexible return policy. Designed as a no-hassle return experience, Amazon's policy has received favorable reviews for its ease and convenience. However, this same flexibility has also led to return fraud, as some customers exploit the policy for unethical gains. This issue of return fraud is increasing, and it has become one of the major hurdles for every retailer, without being an exception for Amazon.
In recent years, Amazon has increasingly adopted AI technologies to combat return fraud and protect the integrity of its flexible return system and customer as well as to make it convenient for them. AI tools such as predictive analytics, machine learning, and NLP are used to identify abnormal return patterns, including recurrent returns and false claims, and returns of used or damaged goods as potentially fraudulent activities. Return fraud represents a growing financial threat to e-commerce businesses, costing the global retail industry over $24 billion annually, primarily through practices such as wardrobing, false claims, and serial returns. In Amazon's ecosystem, the scale of returns, especially during peak seasons, compounds these challenges, forcing the company to seek intelligent, scalable deterrents.
AI systems have emerged as a cost-effective solution to address this issue. AI monitoring refers to the use of automated technologies including behavior tracking, NLP, and predictive algorithms that detect unusual return behavior patterns and help platforms flag or deter potentially abusive activities by integrating real-time behavior tracking, risk scoring algorithms, and NLP-based fraud flags, platforms can detect and prevent fraud more proactively (Cheng et al., 2024; Moin, 2024). According to McKinsey & Company (2024), firms that deploy AI-based fraud detection can reduce reverse logistics costs by 15–30%, resulting in substantial quarterly savings and improved operational efficiency. Amazon itself reported a 13% quarterly profit increase in 2024, attributing part of this growth to enhanced AI surveillance systems that optimized return processing and minimized losses from fraud (Paul, 2024). Moreover, AI enables strategic segmentation, where high-risk users are subjected to stricter scrutiny, and loyal customers experience minimal friction — a dynamic that balances economic performance with customer satisfaction (Zhang & Wang, 2023). Thus, the economic justification for AI implementation extends beyond fraud prevention to encompass broader financial, reputational, and logistical benefits. This study aims to investigate

the role of Artificial Intelligence (AI) in identifying and preventing return fraud on Amazon, while also examining the behavioral motivations behind consumers' exploitation of flexible return policies

1.1. Amazon's flexible return policy

Amazon's customer satisfaction is partly derived from the company's flexible return policy, which allows buyers the easy return of most products within 30 days of purchase. The smoothness of the process allows customers to initiate returns online, print the return labels, and select various return options, among which are drop-offs and pickups. In addition to the foregoing, this easy-to-go-through experience has kept the reputation of Amazon as a customer-centric company, which is creating an all-happy shopping experience wherein buyers who feel confident they can return a product very easily shop.

However, because of the leniency of this policy, it does create practical challenges for Amazon, as this opens a door for some customers to indulge in what may be called return fraud. These might include returning used or damaged merchandise, serial-returning items without a genuine reason, and, in some cases, claims about a product defect.

1.1.1. Easy returns

Amazon often has lots of products it ships with free returns. For example, Goetz, J. (2020) explains how providing free returns on some products is important for customer value. Accordingly, the kind of value is providing customers with returned products at no cost, which may cause an increased tendency for return fraud.

1.1.2. Refunds and replacements

Amazon provides refunds and replaces items that have been returned; in most cases, it often does without requiring the customers to return the original item for some inexpensive goods in such a way that Lane, M. (2021): This could very easily be fraud as customers use stolen or counterfeit goods and then receive refunds without returning the product. More so, no-return conditions for some kinds of products, especially smaller, less-expensive items, could be taken advantage of by customers.

1.1.3. Specific return policies for product categories

Some product categories that might have certain return policies include Lane, M. (2021). electronics, personal care products, and open software that have specific return policies and exceptions, like a restocking fee charge or returnable in new condition only. Thus, the company prevents a certain category of customers; however, a customer can still try returning opened electronic or used personal items using false claims especially if they have laundered the restrictions.

1.1.4. Holiday return policy

Any item bought during the peak shopping holiday season usually continues to accrue long return windows, adding to many of its items a return period into the first week of January. This not only helps increase business during the holiday period and gives enough time to customers, but also allows the possibility

1.1.5. Simple online returns procedure

In the words of Zengler, T. (2020), Amazon has a sweet online return process that allows customers to initiate returns and print labels, and schedule pickups for their return items. This means that it is convenient, makes the process for entering a claim for return much easier in a legitimate sense, for fraudulent customers, that is, easy, and increases the chances of return fraud.

1.2. Role of AI in preventing return fraud

To keep the return policy very flexible on Amazon, Artificial Intelligence (AI), as an advanced technology, is very much involved in slashing the return fraud by customers. AI tools like machine learning or predictive analytics are formulating a pattern of customer return behavior in terms of how often, the reasons, and the types of products returned by analyzing huge numbers of datasets. These are the systems that could detect an anomaly, such as multiple returns for reasons from a customer's response to a message on many returns of items. For this, the company ends up flagging the activities as suspicious before they get out of control. This proactive way of monitoring ensures that the returns are legitimate and goes a long way in reducing fraud while at the same time stitching together a balance between customer satisfaction and less fraud for the company (Zengler, 2020).

The other factor is not only Natural Language Processing (NLP) and image recognition, as AI that increases the capacity of Amazon further in fraud detection. NLP is useful in understanding the reasons for returns provided by customers, which would generally include the inconsistency or suspicious claims in identifying the false damage reports (Williams, 2020). Image recognition scrutinizes the overall condition of returned items and assesses uploaded pictures for anomalies such as improper usage and condition (Goetz, 2020). By this combination of tools - AI, predictive analytics, and behavior tracking - Amazon is able to enforce dynamic return policies for individual customer behaviors, maintaining a fine balance between convenience and fraud prevention measures (Beitner, 2021).

1.3. The application of AI in the detection of return fraud

1.3.1. Anomaly detection

Zengler, T. (2020). AI systems use machine learning algorithms to monitor customer return behaviors over time, flagging any unusual activities such as frequent or high-value returns. Such anomalies are often found to indicate return fraud.

1.3.2. Predictive analytics

Beitner, A. (2021). AI utilizes predictive capabilities that model a customer's history regarding returned items, types of products, and reasons provided for return to measure the risk of a return being fraudulent. It helps in predicting which returns may turn abusive (e.g., serial-returners).

1.3.3. Risk scoring and flagging system

Koller, D. (2020, January 23). AI assigns a risk score to each return based on frequency, item value, and the associated return behavior. High-risk returns are flagged for manual review or are simply rejected.

1.3.4. NLP-return reason analysis

Williams, J. (2020). AI applies natural language processing to analyze the return reasons given by the customer. NLP can flag discrepancies or suspicious wording when helping to catch fraudulent claims (e.g., false damage reports).

1.3.5. Image recognition and computer vision

Goetz, J. (2020, February 7). In certain returns, the customer must upload images of the product being returned. Computer vision tools powered by AI are used to analyze these images and assess the product's condition (i.e., signs of use, damage, or whether it has been opened or used).

1.3.6. AI-powered chatbots and virtual assistants in the return process

Lane, M.(2021). I-chatbots would assist customers in the return process while gathering returns data, and their usage for Amazon to find trends and identify possible fraud. Data analysis of fraud once items have been used over the holidays, such as with clothing or gift items being returned

1.4. Customer returns (CRB)

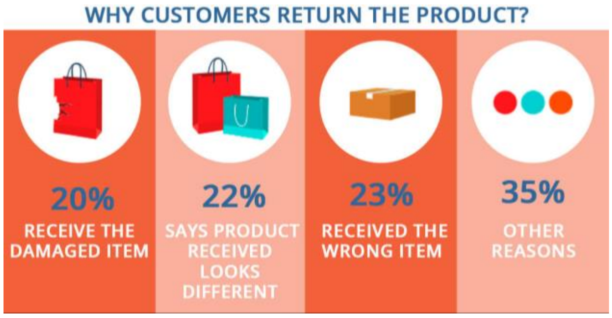

Fig 1: Reasons for Customer Returns in E-Commerce (Source – eStore factory)

As illustrated in **Fig 1**, customers most commonly return products due to damage, mismatch, or delivery errors. The return behavior of customers has long been a huge concern for any e-commerce company, Amazon included, since it incurs considerable logistical expenses and can influence customer satisfaction or seller performance. As Amazon continues to adopt AI applications to refine return policies and project consumer return trends, it would be essential to see how such technological inventions affect customer behavior before and after AI implementation. While AI can help consumer returns with predictive insight and customized experiences, the flipside in this scenario is the ethics surrounding customer returns.

Cheng et.al. (2024) analyze a dataset of 90,962 returns for 73,965 products across 34 product categories, representing all major categories on Amazon.com. The breakdown of return reasons is as follows: 63,828 returns (70.2%) were due to product-related issues, such as defects; 17,682 returns (19.5%) were related to merchant issues, including discrepancies between what was ordered and what was received or missing items; 6,769 returns (7.4%) were customer-related, often due to items no longer being needed or wanted; 2,212 returns (2.4%) were carrier-related, and 471 returns (0.5%) fell under other categories.

1.4.1. Crucial information (image, videos, sizing guide)

High-quality images, videos, and detailed sizing guides are essential in helping customers make informed decisions, and they also play a crucial role in reducing product returns (Ailawadi, K. L., & Farris, P. W., 2016). AI tools can enhance the accuracy of sizing guides based on customer feedback and previous returns. When these resources are clear and helpful, they can reduce the likelihood of returns due to incorrect expectations.

1.4.2. Quality

Product quality is one of the most significant reasons for returns. (Zhang and Zhao, 2018) Higher perceived quality leads to lower return rates, whereas even minor quality issues can lead to significant return spikes. AI can help predict potential quality problems by analyzing customer reviews and historical return data, enabling sellers to address these issues proactively before they result in high return rates.

1.4.3. Defective product

A significant portion of returns is due to product defects, such as damage, malfunction, or failure to meet expectations (Reinartz & Kumar, 2019). AI can mitigate these returns by identifying products that are more likely to be defective early in the supply chain, allowing sellers to flag defect-prone items and reduce the likelihood of returns due to product faults.

1.4.4. No longer needed

Customers who lose interest or no longer feel attached to a product after purchase are more likely to return it, even without a defect or quality issue (Liu & Wei, 2020). This can happen after an impulsive purchase or as a result of changing needs. AI can help reduce this type of return by offering more personalized product recommendations that better align with customers' long-term needs and preferences, rather than fostering impulse-driven buying behaviors.

1.4.5. Lost interest

Over time, customers may lose interest in a product they initially found appealing, especially after receiving the product and reflecting on it. AI-powered recommendation systems can help sustain customer interest by suggesting products that better align with their evolving preferences, thus reducing returns caused by loss of interest.

1.4.6. Late delivery

Late deliveries can lead to higher return rates, especially when customers receive products after they were needed, leading to dissatisfaction (Saghiri & Zolfagharian, 2017). AI tools can help by notifying customers about potential delivery delays before the product arrives, potentially preventing returns that occur due to late arrivals.

1.4.7. Impulsiveness

Impulse buyers are more likely to return products due to regret or second thoughts after making an emotional purchase, which is a significant factor contributing to online return rates (Dholakia & Zhao, 2019). AI algorithms can reduce impulsive purchases by suggesting more thoughtful, need-based items and even offering reminders or restrictions that align with customers' previous buying behavior or preferences.

2. Review of literature

2.1. Theoretical background of customer product returns behavior

Lee, D.H. (2015). Strangely, the products being produced in recent times are better than those of the past. Yet the amount of returns for such products has increased; thus, people return products before they experience dissatisfaction, even though they do not have any defects. Ironically, the quality of the products has improved, while their returns have increased. This can mean that there are still issues that have not been unravelled regarding the reasons behind the return of products.

Urbanke et.al. (2015) developed a model for predicting customer returns using an innovative dimensionality reduction technique. Their experiments, conducted on 1,149,262 products purchased from a major FGerman online fashion retailer between July and November 2014, revealed a return rate of 57.3%. The model utilized a feature set that included product-level features (e.g., brand, color), basket-level features (e.g., time of purchase), and customer-level features (e.g., historical return rate). The authors demonstrated that the model could accurately predict instances where the likelihood of return was extremely high, even before the purchase was made.

Powers and Jack (2015) identified product and emotional dissonance as key triggers for returns. Product dissonance occurs when customers feel that their recent purchase was unnecessary or that they chose the wrong product. Emotional dissonance refers to psychological discomfort, often resulting from dissatisfaction with the purchase. The authors proposed that product dissonance can lead to emotional dissonance, prompting customers to return the product to alleviate this discomfort. In a study of 308 customers from physical retailers (Walmart and Target), they found a positive correlation between product dissonance and emotional dissonance. The study also explored two primary reasons for returns: "expectation not met" and "found a better product or price." Both reasons were positively correlated with emotional dissonance, which in turn was positively correlated with return frequency. Additionally, these two return reasons showed a significant correlation with each other.

Pei, Z., & Paswan, A. (2018). At the same time, those customers with more impulsive buying behaviors will be the ones who will be inclined to return the product because they shop on the spur of the moment and are less likely to rationalize their return after the purchase. However, customers with a desire for product uniqueness will have lesser tendencies to return the product. Hence, customers acting in bad faith are more likely to exploit the retailer's generalized return policy and return for opportunistic gains.

Ertekin, N. (2018) states that it might be difficult or guilt-ridden to return a product. It makes sense to suppose that thoughts and feelings may be at odds: one can feel bad about returning something even though they admit it was simple to do so, or the other way around.

Rintamäki, T., Spence, M.T. et.al, (2019) Qualitative insights confirmed that factors like money, convenience, pressure, and guilt drive perceptions around the returns experience. The quantitative findings indicate that the returning experience affects return satisfaction for both planned and unplanned returners, and return satisfaction itself tends to influence overall satisfaction and WOM.

Lin, D et al,(2020). It was confirmed from the findings that the most influential factor in online shopping returns is the return intention of the product, with a direct effect of 0.63, and the flexibility of return (logistics service) has a direct effect of 0.49.

Guo and Chang (2021). When customers purchase products through online business-to-consumer platforms in Taiwan, the government permits them to return them for any reason within seven days; however, it is not permitted to return damaged or used goods. However, consumers misuse this consumer protection regulation by submitting ambiguous return requests with false complaints.

Altug, M.S. et.al., (2021) In fact, freedom of returns can sometimes create counterproductive opportunistic consumer returns by customers purchasing an item with no intention of permanent retention-and then using it briefly, if not for one time.

Chang, H.-H.; Yang, T.-S. (2022). In practice, a flexible return policy set up by vendors to attract customers and provide them with a better online customer experience (OCX), while designed to enhance customer satisfaction and trust, may inadvertently encourage a subset of consumers to exploit this system through unethical return practices

Wang, Y.; Yu, B.; Chen, J (2023) The findings about online review factors show that, through the mediation of cognitive and emotional dissonance, aggregated indicators (such as review consistency) and individual review content (such as the emotions expressed in reviews) play crucial roles in influencing customers' intention to return.

Urbanke, Hachimi, and Mayhew (2024) conducted a comprehensive systematic review of forecasting methods in e-commerce returns, highlighting the transformative role of AI-based time-series models and machine learning in predicting return volumes. Their findings reveal that such forecasting tools not only optimize inventory and logistics but also serve as early warning systems for potential fraud. By detecting unusual return spikes or patterns, retailers can proactively address policy fraud. This dual benefit of improved operational efficiency and fraud prevention aligns closely with the themes of our study, reinforcing the value of AI-driven insights in return policy design.

Satija and Singla (2025) undertook a bibliometric review of AI adoption in e-commerce, highlighting four key themes: customer experience, supply chain management, fraud prevention, and ethical deployment. Their analysis indicates a strong shift toward personalized policies and segmentation driven by AI, supporting our findings that tailored return rules and surveillance can deter fraudulent behavior while fostering customer satisfaction. This framework bolsters our recommendation for dynamically segmented return policies based on AI-driven risk profiles.

2.2. Theoretical background of AI (detection of return fraud)

Amazon (2019) Artificial Intelligence aided in anticipating the trend of returning goods, thereby avoiding erroneous returns from happening. The prediction happens to synchronize what the customer prefers with what is offered.

Wang, Y., & Liu, Z. (2020). AI systems have cut return rates generously by ensuring precise product descriptions and personal experience. AI-powered recommendation engines, virtual assistants

Johnson, H., Lee, J., & Smith, A. (2018). AI algorithms have been reducing return fraud by identifying patterns that look suspicious, thus improving the return process generally, while these initiatives are designed to decrease return rates.

Vogue Business (2024) Amazon has implemented several AI-driven initiatives to enhance customer experience and reduce product return rates. Notably, the "Fit Insights" tool utilizes large language models to analyze customer feedback on fit, style, and fabric, providing brands with actionable insights to improve product sizing and reduce returns

Amazon (2024) The AI will detect product defects in the products produced by Project.pi. If a product error is detected, the respective product will still be sent to the customer, but it will be marked as faulty.

Moin, D. (2024) Cheng, H.-F.(2024) Information from industry reports shows that the average return percentage in Amazon cases can reach between 5% as well as 15%, with electronics and clothing displaying extraordinarily high rejection rates, almost 40%.

Paul, K. (2024). Adding together total income from precedents with this new claim, Amazon grew revenue by 13% to an all-time high of 143.3 billion in Q1 2024. Although this is a good sign for the company, a lot of success can be attributed to reduced product returns from having incorporated AI.

McKinsey & Company's (2024) industry report highlights the substantial economic value generated by AI integration in retail operations. The report estimates that AI-driven fraud detection, returns forecasting, and inventory optimization can reduce reverse logistics costs by 15–30%, resulting in significant quarterly savings for large retailers. These financial benefits are particularly relevant to the issue of return fraud, where proactive AI surveillance reduces operational loss while improving decision-making efficiency. The findings support the argument that AI adoption is not only a technological upgrade but also a strategic cost-saving investment, especially when implemented at scale across high-return product categories. This perspective aligns with the present study's economic framing, reinforcing the dual function of AI as both a fraud deterrent and a value-creating asset.

Fariha et al. (2025) present a timely and detailed examination of machine learning techniques applied to fraud detection within transactional and accounting domains. Their review identifies strengths and limitations across supervised and unsupervised methods—such as Random Forests, SVMs, and neural network architectures—demonstrating how these models enhance detection accuracy while maintaining operational efficiency. Notably, the authors highlight the necessity for model transparency and explainability, which parallels the need for ethical AI in e-commerce fraud systems to preserve consumer trust. Their findings offer methodological insights easily transferable to the detection of return fraud in platforms like Amazon.

Simatupang (2025) synthesizes the ethical, organizational, and technological dimensions of AI in accounting and finance, stressing the importance of explainability, bias mitigation, and robust data governance. Although centered on financial institutions, these themes are directly applicable to e-commerce fraud detection, where consumer trust is crucial. By emphasizing transparency and regulatory alignment, Simatupang's work underscores how ethical AI deployment can balance technological effectiveness with societal responsibility, mirroring the safeguards needed for AI in return for fraud prevention.

Ilugbusi and Dorasamy (2025) discuss how machine learning and Natural Language Processing are reshaping fraud detection and workflow automation in accounting. They emphasize real-time analytics, audit trail integrity, and precision in anomaly detection, which translates well to e-commerce fraud control. Their study provides a strong theoretical bridge for our research, highlighting how accounting-grade AI mechanisms can be repurposed to monitor consumer returns, evaluate policy compliance, and maintain data integrity—core concerns in preventing return fraud.

3. Research methodology

3.1. Introduction

The research adopts a quantitative methodology to analyze the influence of Artificial Intelligence on return fraud detection for Amazon and to explore customers' reasoning behind abusing flexible return policies. Data were obtained through the administered questionnaires, statistically analyzed, and modeled to identify patterns and validate hypotheses concerning return behaviors and AI awareness.

3.2. Need and importance of the study

The growing trends in e-commerce, as one of the factors, have enhanced return fraud. Such return fraud poses many relevant challenges to various platforms such as Amazon. Though the flexible return policy of Amazon is a way of promoting customer satisfaction and loyalty, it also exposes it to the risks of return fraud (Davenport et al., 2020).

This study is important for many reasons. Financial Impact: Return fraud costs retailers billions every year (Janakiraman, Syrdal, & Freling, 2016). An understanding of how AI can effectively reduce the avenues of fraudulent returns will further provide the needed guidelines for actionable insights, which can be applied as a way of helping Amazon and other retailers avoid losses. Limited understanding of return policies has been there, with few insights on why consumers defraud them. The study will delve deep into the psychological and behavioral motives of consumers abusing return policies; these insights will provide immense value for marketers and policymakers.

This will show us how the tools of predictive analytics and machine learning can be used to create real solutions to address return fraud. In doing so, it can show Amazon how to balance the prevention of fraud with the need to provide a good customer experience. Global E Commerce Implications: As e-commerce takes in stride and grows with the phenomenon of COVID-19 in its wake, detection and prevention of fraud through AI will benefit not just Amazon but all other online retailers looking to put in place robust systems of fraud prevention.

3.3. Statement of the problem

The increasing return fraud in e-commerce, especially with Amazon's lenient return policy, has created great challenges for them. While creating a good experience for customers, these same policies allow some customers to engage in fraudulent returns, therefore costing them money, inventory, and relationships with sellers. Although AI is a powerful tool for detecting fraud, its potential in curbing return fraud is rarely explored. This research will consider how the return fraud rate can be kept lower by using AI technologies while also giving much consideration to customer-friendly activities and the behavioral motivations behind return fraud.

3.4. Research gap

Despite significant research on e-commerce return policies, there is a lack of focus on how AI can prevent return fraud, particularly within Amazon’s flexible return system. Most of the studies have rather focused on logistic effectiveness and/or policy effectiveness (Janakiraman, Syrdal, & Freling, 2016), with less attention given to consumer behavior related to return fraud. Furthermore, the literature deals mainly with return fraud from the perspective of management (Rao & Narayan, 2018), overlooking AI awareness of consumer behavior regarding it. The only work found that discussed AI potential in retail and its implications in consumer psychology was that of Liang and Huang (2021). Finally, very few studies explored Amazon's return policy with a possible dimension of how AI could prevent fraud within this policy (Davenport, Guha, Grewal, & Bressgott, 2020). Filling these gaps, the present work explores consumer behavior, AI awareness, and policy perceptions, driven towards an integration for optimal fraud detection.

3.5. Scope of the study

Artificial Intelligence (AI) takes center stage with respect to this study in how it helps prevent return fraud in connection with Amazon's flexible return policy. This research will specifically investigate the following:
Consumer Behavior: Understanding why customers take advantage of Amazon's flexible returns, awareness, and motivation for return fraud.
AI Surveillance: Under what conditions might AI tools monitor, detect, and/or eliminate fraudulent behavior in returns without adversely affecting customer satisfaction.
Return Policy Perception: How would a customer consider that a "lenient" return policy or return-policy effectiveness might affect their return?

3.6. Conceptual framework

The conceptual framework depicted in **Figure 2** illustrates the relationships between consumer characteristics, perceptions of return policy flexibility, and awareness of AI monitoring in shaping return fraud behavior. These variables form the theoretical foundation for understanding the behavioral and technological dynamics that influence return fraud in e-commerce.

- Independent Variables: These include consumer demographics (such as age, gender, and shopping frequency), perceived flexibility of return policy, and awareness of AI surveillance. These factors are hypothesized to influence consumer decision-making when considering whether to engage in unethical return behavior.
- Dependent Variable: Return fraud behavior—defined as misuse or manipulation of return policies (e.g., wardrobing, false defect claims)—is the primary outcome being studied.
- Moderating Variable: AI intervention, particularly through tools like predictive analytics and automated fraud detection systems, is modeled as a moderating influence. The assumption is that awareness of AI surveillance enhances perceived risk, thereby discouraging unethical return behavior without alienating legitimate customers.

As shown in the framework, all three independent variables influence a set of behavioral triggers. AI then moderates this relationship by amplifying the perceived risk of detection. Ultimately, the framework suggests that a combination of demographic insight, policy perception, and technological deterrents contributes to a reduction in return fraud and fraud. This structure directly aligns with the study’s regression analysis, which found AI awareness to be a significant negative predictor of return fraud behavior ($\beta = -0.38$, $p < 0.001$).

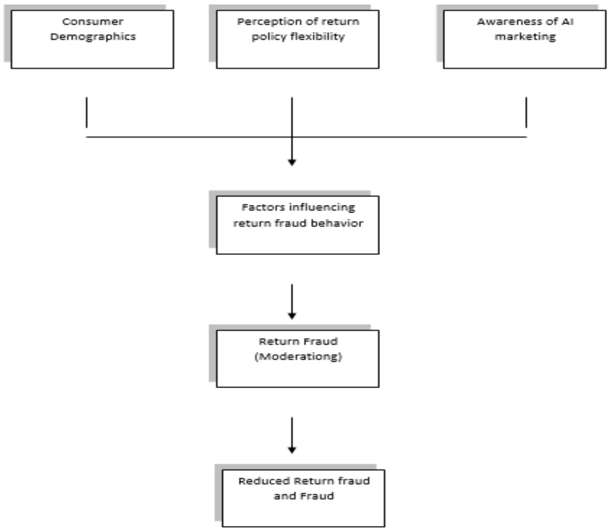

Fig 2: Conceptual Framework of Factors Influencing Return Fraud Behavior (Source: Author)

The consumer characteristics and the perception of the return policy influence whether or not they might commit fraudulent returns. To the extent that consumers are aware that AI technology is monitoring returns, it may deter fraud. Here again, AI systems act as moderators that enhance perceived risk and reduce fraud without harming legitimate customers.

3.7. Objectives

- To assess the role of AI in identifying return fraud and mitigating fraud.
- To analyze the reason that the customer often exploits Amazon's flexible return policy.

3.8. Research design

The present research adopts a quantitative, descriptive, and analytical design and was framed to address the role of artificial intelligence (AI) in mitigating return fraud under Amazon's loose return policy. A survey-based cross-sectional approach was used to gather primary data from online consumers about their return behaviors, awareness of AI technologies, and perception towards the strictness of the policy.

3.9. Sampling

A purposive sampling method was adopted for this study, targeting active Amazon users with prior experience of returning products. A total of 250 valid responses were collected, a sample size chosen based on prior empirical studies involving consumer behavior and AI awareness in e-commerce contexts (e.g., Liu & Wei, 2020; Zhang & Wang, 2023). This number was considered sufficient to allow for reliable descriptive analysis, regression modeling, and chi-square testing with acceptable statistical power.
The respondents were primarily drawn from urban regions in South India, reflecting a high-growth e-commerce market and one of Amazon’s key regional customer bases. This regional focus was selected to capture localized behavioral patterns within a rapidly digitizing consumer economy.

3.9.1. Sample characteristics

Table 1: Summary of Sample Characteristics

Demographic Variable	Category
Age	18–45+
Gender	Male, Female, Others
Frequency of Shopping	Weekly, Monthly, Occasionally
Return Behavior	Frequent, Moderate, Rare

3.10. Data collection method

A structured online questionnaire was designed using Google Forms. The instrument included both closed-ended and Likert-scale-based questions. The survey link was distributed via email, WhatsApp, and social media platforms, focusing on e-commerce user communities. Responses were collected over a period of three weeks. Data was screened for completeness; incomplete or duplicate responses were excluded, resulting in a final usable sample of 250 responses. The questionnaire was pilot-tested with 20 users to ensure clarity and reliability.
It consisted of four sections:
- Demographics (age, gender, shopping habits)
- Return behavior patterns
- Awareness of AI-based monitoring
- Perception of policy strictness and fairness

3.11. Data analysis techniques

- Data analysis was conducted using SPSS and Excel. The analysis process included:
- Data Cleaning: Removal of incomplete or inconsistent entries.
- Descriptive Statistics: Used to summarize demographics and shopping/return behavior.
- Chi-Square Test: To examine the association between demographic factors (e.g., shopping frequency) and return fraud.
- Regression Analysis: To evaluate the influence of AI awareness and perceived policy strictness on return fraud behavior.
- Reliability Testing: Cronbach's alpha was calculated for Likert-scale items, with all constructs exceeding the acceptable threshold of 0.70, indicating good internal consistency.

3.12. Source of data

This research employs both primary and secondary sources of data. An online questionnaire, sent to a sample of Amazon customers who have experience with product returns, served as the primary data collection method. The online survey included demographic details, behavior on product returns, perception of Amazon's return policy, and knowledge regarding AI monitoring. Secondary information was obtained from scholarly articles, industry reports, and case studies pertaining to theft in e-commerce, applications of AI, and consumer behavior studies.

3.13. Pilot study

A pilot study was conducted for the assessment of the clarity, reliability, and applicability of a questionnaire before undertaking full-scale data collection. The pilot involved 20 respondents, who would be able to fill in survey forms and had experience with product returns after frequent shopping on Amazon. The feedback collected was employed in refining question wording, response options as well and flow. Internal consistency of the instrument was evaluated by means of Cronbach's Alpha, with most sections (e.g., AI awareness, return behavior, policy perception) having reliability scores indicating that the items were coherent and suitable for analysis above an acceptable value of 0.70. Based on these, minor improvements were made in the final survey for improving validity and easier comprehension.

3.13.1. Reliability test

Table 2: Reliability (Cronbach's Alpha) Test Results

Construct	No. of Items	Cronbach's Alpha (α)
Awareness of AI Monitoring	5	0.82
Perceived Return Policy Strictness	4	0.79
Return Behavior	6	0.85

A Cronbach alpha value for all three constructs is measured above 0.70, indicating a high degree of internal consistency and hence reliability for the scale items used in the questionnaire. More specifically:
AI Monitoring Awareness ($\alpha = 0.82$): Denotes strong internal coherence among items measuring how well respondents understand or are aware of AI monitoring during the return process.
Perceived Strictness of Return Policies ($\alpha = 0.79$): Denotes that this scale reliably measured respondents' perceptions of the rigidity or leniency of Amazon's return policies
Return Behavior ($\alpha = 0.85$): Denotes a high degree of internal consistency among items that measure respondent history and patterns of return behavior.

4. Data analysis and interpretation

4.1. Demographic profile

Table 3: Demographic Profile of the Respondents

Attribute	Categories	Frequency	Percentage (%)
Age Group	18–25 years	75	30%
	26–35 years	112	45%
	36–45 years	50	20%
	46+ years	13	5%
Gender	Male	130	52%
	Female	120	48%
Frequency of Online Shopping	Once a month	62	25%
	2–3 times a month	125	50%
	Weekly	63	25%

Interpretation: From above the table, demographic analysis reveals that a majority of the respondents (45%) belong to the age group 26-35 years. It appears that young adults are the most active participants in online shopping and are quite likely to engage in the behavior concerning returns. The next category is around the age of 18-25 (30%), which suggests that this group also has significant involvement in e-commerce activities. The rest of the segments are composed of a smaller number of participants above the age group of 46 years, which comprised only 5%, while the remaining 20% belonged to the age groups 36-45. Again, highlighting a lesser engagement from older consumers.
This means the sample is rather well-gender balanced, with 52 percent male and 48 percent female respondents, instead, distributing evenly and potentially eliminating the gender bias angle in behavioral insights. Coming to the aspect of frequency in online shopping, it can thus be said that 50 percent of respondents purchase online 2-3 times a month. The activity frequency, therefore, proves to have a moderate but continuous involvement with e-commerce platforms. Meanwhile, 25 percent shopped weekly, thus being a very highly active consumer segment, whereas the other remaining 25 percent shopped just once a month, thus showing casual users of the services.

The spread under this probably indicates that it is a sample well diversified concerning the frequency of shopping, which can further shed light on the differentials in return behavior.

4.2. Behavioral insights

Table 4: Shows Behavioral Insights of the Respondents

Factor	Categories	Frequency	Percentage (%)
Main Reasons for Return	Wrong product received	105	42%
	Product defect	90	36%
	Change of mind	55	22%
Awareness of Return Fraud Policy	Yes	175	70%
	No	75	30%
Perception of Amazon's Return Policy	Very flexible	163	65%
	Moderately flexible	72	29%
	Strict	15	6%

Interpretation: This table shows that the principal cause of returns was wrong product received (42%), followed by defective product (36%), and change of mind (22%). Most returns indicated a fulfillment issue or product quality issue. A huge majority of 70%, respondents know of the return fraud policy of Amazon, indicating pretty general consumer awareness. Besides, most of the respondents (65%) consider the return policy of Amazon as very flexible, which may also lead to some kind of fraud of the policy.

4.3. Inferential analysis

Chi-Square Test - To test a relationship between Shopping Frequency and Return Fraud Behavior.

Cross-tabulation for Shopping Frequency vs Return Fraud
Shopping Frequency
Once a month
2–3 times a month
Weekly

Chi-Square Test Results:

Table 5: Shows the Relationship between Shopping Frequency and Return Fraud Behavior

Test	Value	df	p-value	Result
Pearson Chi-Square	12.65	2	0.0017	Significant (p < 0.05)

H_1: There is a significant relationship between consumer demographics (age, shopping frequency) and the likelihood of engaging in return fraud.
Interpretation:
The Chi-Square test reveals that shopping frequency and fraud of returns are statistically significantly related ($\chi^2 = 12.65$, $p = 0.0017$). Since the p-value is smaller than 0.05, we rejected the null hypothesis and accepted the alternative one (H_1), supporting the notion that customers shopping more frequently are more likely to commit return fraud. Therefore, shopping frequency is an important determinant of the prediction of return-related misbehavior.

4.4. Regression analysis

Analyze how awareness of AI monitoring, perceived strictness of return policy, and frequency of returns affect return fraud behavior.

Table 6: Awareness of AI Monitoring, Perceived Strictness of Return Policy, and Frequency of Returns Affect Return Fraud Behavior

Predictor	Unstandardized Coefficient (B)	Standard Error	Beta (β)	p-value
Awareness of AI Monitoring	-0.42	0.08	-0.38	0.000
Perceived Strictness of Return Policy	-0.29	0.10	-0.25	0.004
Frequency of Returns	0.51	0.07	0.42	0.000

R	R^2	Adjusted R^2	F-value	p-value
0.58	0.336	0.330	41.25	0.000

(R^2 = 33.6% of the variance in return fraud is explained by these three predictors
H_2: Awareness of AI monitoring has a significant negative effect on return fraud behavior.
H_3: Perceived strictness of Amazon's return policy significantly influences return fraud behavior.
Interpretation: The regression analysis yielded statistically significant results ($F=41.25$, $p<0.001$) and an R^2 value of 0.336, which suggests that approximately 33.6% of the variance in return fraud behavior is accounted for by AI monitoring awareness, perceived strictness of policy, and frequency of returns.
The awareness of AI monitoring is a statistically significant negative predictor of return fraud ($B=-0.42$, $p<0.001$), providing statistical support for H_2. This suggests that greater awareness of AI reduces the incidence of fraudulent returns.
Perceived strictness of return policy is again a statistically significant negative predictor of return fraud ($B=-0.29$, $p=0.004$), thereby supporting H_3. Customers who perceive the return policy as having stringent requirements are less likely to abuse it. The frequency of return is significantly positively correlated to return fraud ($B=0.51$, $p<0.001$), showing that those who partake in more frequent returns are more likely to misuse the return policy.
Summary:

- Younger and frequent shoppers are more likely to engage in return fraud.
- Customers aware of AI monitoring behave more cautiously.
- Return policy strictness moderates abusive behavior without losing overall customer trust.

- AI can strategically reduce fraud while maintaining flexible customer services.

5. Findings of the study

High AI Awareness Reduces Return Fraud
Respondents aware of AI monitoring were much less likely to return fraud, suggesting that such awareness may deter potential actors from abusing the policy.
Demographics Influence Return Behavior
The younger the consumer and the more s/he shopped online, the more likely it is that the return behavior was exploitative.
Policy Perception Affects Behavior
Those respondents who saw Amazon's return policy as too liberal were more likely to abuse it, so a fair balance in the policy design will be called for.
AI Seen as a Fair Tool
The majority of participants agreed that AI use in fraud detection is acceptable, provided privacy and transparency are maintained.
Common Patterns of Fraud Identified
Wardrobing and falsely identifying products as defective were the most commonly cited frauds.

6. Conclusion

This study provides strong evidence that artificial intelligence plays a crucial role in identifying and reducing return fraud in e-commerce platforms such as Amazon. The findings indicate that consumers with higher awareness of AI monitoring are significantly less likely to engage in unethical return behavior, suggesting that transparency about surveillance technologies may act as a behavioral deterrent. Additionally, demographic insights, particularly age and online shopping frequency, were found to influence return tendencies, while perceptions of overly lenient return policies were directly linked to increased fraud. Importantly, the majority of respondents expressed acceptance of AI fraud detection, provided it is implemented ethically, with privacy safeguards and transparent communication. This research also emphasizes the necessity of embedding ethical standards—such as fairness, algorithmic explainability, and regulatory compliance (e.g., GDPR, DPDP Act)—into AI design and deployment. Overall, this research contributes to the evolving discourse on AI in retail by demonstrating that ethical and adaptive AI frameworks can deter return fraud while preserving customer trust.
These insights serve as a valuable foundation for practitioners, policymakers, and future researchers to refine AI-enabled fraud prevention systems that are both effective and ethically grounded.

7. Policy recommendation

To strengthen the effectiveness and public trust in AI-driven return fraud detection, it is recommended that platforms like Amazon adopt a structured regulatory and ethical framework for AI usage. This includes communicating to customers when and how their return behavior is monitored through automated systems, ensuring transparency in data usage. Importantly, the implementation of AI must align with established data protection regulations, such as the General Data Protection Regulation (GDPR) in the EU and India’s Digital Personal Data Protection (DPDP) Act (2023). These frameworks emphasize consent, purpose limitation, and data minimization, which should guide how consumer return data is collected and analyzed. Furthermore, industry-wide standards could be developed for fraud detection AI, similar to financial auditing guidelines, to ensure fairness, avoid discriminatory targeting, and promote ethical AI deployment. Retailers should also consider third-party audits and algorithmic explainability tools to enhance accountability in automated decision-making processes related to returns.

8. Suggestion

Based on findings, Amazon increases the transparency surrounding the artificial intelligence (AI) techniques it uses to monitor return behavior. When consumers know that AI tools are being used to detect fraudulent return attempts, it acts as a psychological deterrent while not hampering the experience of genuine shoppers. In addition, the communication about AI detection systems instills trust while deterring unethical practices.
Moreover, Amazon can instill return segmentation based on customer response. For example, long-term customers with mild return behavior may be accommodated with a more permissive policy, while accounts exhibiting suspicious or frequent return behavior may be held to stricter controls. This more targeted approach to encompass return policies helps minimize fraud without unnecessarily hindering genuine users.
Also important is educating customers regarding the misuse of return policies. Amazon could implement very brief in-app messages, email campaigns, or warnings at checkout that emphasize what is considered return fraud and enumerate the potential fallout. These awareness-raising initiatives could stimulate responsible behavior in customers.
With that, the AI system should be routinely improved with behavioral analytics to determine changing patterns of fraud. Data privacy must remain at the forefront in the development of these tools to ensure ethicality and customer confidence.
The last step would be fortifying collaboration with the third-party vendors to align return processes and fraud detection. If policies are aligned and relevant information is shared, Amazon and its partners can work together on minimizing fraud and strengthening the credibility of the platform.

9. Future research directions

Given the evolving nature of AI applications in e-commerce, future research could examine how fraud detection systems perform across different product categories, such as fashion, electronics, or consumables, where return behavior may differ significantly. Additionally, longitudinal studies could investigate how ongoing AI monitoring influences consumer trust, perceptions of fairness, and platform loyalty over time. Comparative studies across different platforms or regional markets may also reveal how variations in return policy design or AI transparency affect user behavior and policy compliance. These directions would deepen our understanding of AI's role in balancing fraud prevention with customer experience in diverse digital retail contexts.

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