Automated Return Reason Classification and Reverse Logistics Optimisation: AI-Driven Frameworks for Retail Returns Management Efficiency

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1. Introduction

Managing returns effectively is a pressing issue for both customers and retailers alike. The growing volume of returns, fluctuations in demand, and increasing customer habits of over-ordering make the flawless running of returns management an extremely complex task for retailers. Such retailers have to invest a lot of time and effort in returns management to ensure that more business comes their way; without this, they are bound to only focus on customer service. However, only one-fourth of the returns are a clear sign of inefficiency in the internal processes and the companies' responsibility to manage returns and gain customer trust. Even more worrisome is the fact that the majority of these returns are goods that are in perfect condition. In fact, inefficient returns management is estimated to take away about 3-5% of the annual sales revenue! Recent estimates suggest that 8 out of 10 returns are due to online purchases, prominently within the retail sector.

In the retail sector, a key concern of the operational mindset is ensuring that their sales-to-return ratio does not increase; that is, many sales relative to few returns is a fact they would like to boast. The key to achieving this, apart from other supply chain management initiatives, is improving the returns management process, since the returns management process is not seen as a customer service process by those at the operational helm. With the proliferation of the pandemic, the returns volume is bound to increase. To manage this better and reduce the impact on bottom lines and be more customer-centric, the future is AI and ML, where this industry has been left behind by its industrial counterparts.

1.1. Background and Significance

Returns management has always been a nuisance for retailers. It causes operational inefficiency, sometimes forces companies to stop online selling, and brings about high economic costs. Return rates, or reverse logistics, have skyrocketed in recent years, in conjunction with great business profitability and customers getting the upper hand. Returns management is not a minor issue in retail logistics at all, but it can affect retailers' profitability and operational costs drastically. Return rates can climb even higher if we think of fashionable products, fashion enthusiasts, non-impulse buyers, failed deliveries, and unattractive and misleading online advertisements.

This may lead to an unsuccessful upsurge in the reverse flow of supply chain goods. Strategically and tactically, customers will go to their preferred stores; they will patronize retailers having the easiest return procedures. They might take to social media and even post pictures of items or share their worst experiences in returning products if they are not satisfied with after-sales service. Thus, poorly managed retail returns can certainly impact future sales and branding negatively. Using artificial intelligence in returns management guarantees the above suspension level in removing the importance of the returns level by end users, especially customers who buy online. Thus, the challenge of returns management culminates as far as end users are concerned. For the end business house, things could not exacerbate any further. They are pending on how effectively they handle it. They aren't even influenced in such circumstances that are beyond them. They might have minimized their investment in handling every outcome of returns by purchasing a product or bearing some financial repercussions. With the arrival of artificial intelligence, indeed, the challenge has been addressed to their benefit. Given the huge costs involved, some retailers are satisfied with strategies based on 'preventionism.' They try to block such returns and exchanges by customizing or manufacturing to meet customers' needs.

Given these concerns, there is a need for leveraging advanced technologies to transform the retail returns process. In the following section, we discuss the major different processes and products developed and launched by companies today.

1.2. Objective and Scope

The objective of this essay is to provide a detailed view on the role of AI in the area of managing returned items in retail. The essay has essentially three parts. In the first part, we highlight the various challenges that are currently faced by retailers concerning the handling of returned items. The second part of the essay focuses on the various AI systems and technologies and how they can specifically address the various challenges of reverse logistics. In a concluding part, we will provide a short reflection on the managerial implications of implementing AI in this area.

Scope: In the context of retail operations, returned items skyrocketed due to generational shopping habit changes and technological advancements. A rise in customer orders leads to a surge in volumes of returned parcels to be handled by retailers. Retailers face a number of hurdles when managing the returns and need to find efficient solutions. The amount of returns prompted a considerable amount of research and analysis in the area, partly fueled by increasing public awareness of environmental issues and associated economic waste. We will provide an overview of the state-of-the-art research in the area of retail reverse logistics. However, we do not intend to discuss consignment systems, deposit-refund systems, or the collection and recycling of goods, nor do we address the specific requirements within various industry sectors in detail. Our analysis of the latest developments in the topic area relates exclusively to the possibilities provided by artificial intelligence.

The objective of our essay is to discuss the application of AI systems and technology to develop management practices, technologies, and integrated processes for the efficient management of returned items. We limit our discourse intentionally to systems managed by AI and do not consider traditional systems. We will also focus exclusively on the application of AI in the retail sector and industry, recognizing that other industrial sectors are also faced with challenges that could benefit from insights. Moreover, we are focused on the handling of physical goods and not the management of the reverse processes of services. Finally, we introduce our discussion considering that there are three issues at stake in the technology adoption of handling returns: cost efficiency, customer satisfaction, and sustainability. It will be of particular interest to explore to what extent artificial intelligence has been recognized to address the challenge of 'reverse' supply chain logistics, and therefore either solutions have been proposed or are being researched. The systemic review should provide a coherent picture of different directions that research is following and perhaps a broader understanding of the development. Furthermore, the aim of the paper is by no means comprehensive and may not incorporate all important articles available, but provides a diverse view from different journals in about the last five years. This recent time span will be particularly useful and relevant to grasp the current state of the art and the future direction of the field.

2. AI Applications in Retail Returns Management

AI has the potential to bring revolutionary changes in retail returns management. Keeping in view the significant role of returns in e-commerce, extending automation possibilities in returns initiation is a must to make the complete cycle less reliant on manual intervention as it is today. Products are dispatched, and markings can start; addressed returns come to the distribution center locations, stock adjustments could be made, and maybe in some individual cases, items could be resold, for instance, as open box items. While handling returns is manual, higher error rates are just a matter of time. Incorrect addressing, not adding returned items, justifying a profit reduction to the organization, and confusing customers who can affect any future purchase are some of the impacts. Reducing practical work as much as possible and even addressing items that did not return home automatically might improve the products in the distribution centers for open box purposes.

Returns are a major pain point in e-commerce. However, a return in itself is not that bad. What is? That is the increasing return rates several years in a row, leading to a significant reduction in net sales, as well as predicting these dynamics and being prepared to handle them. This trend could be the start of bankruptcy or at least a call for immediate action regarding your strategy. Predictive analytics could be a big help here, among other things. Better understanding patterns regarding the group it belongs to can refine profit margins on smaller segments over time. Providing a state-of-the-art returns experience is not an add-on benefit for customers; it is a requirement to reach higher sales in the world of online trading. Therefore, the customer portal can still have a return prior page even if the return was initiated automatically. This automatic behavior linked to initiations will be an efficient item for 'in-system resell' decisions. You can offer items on a listing platform to increase chances to resell if the items have been returned directly to addresses. Manually, there is no time to list items due to manual labor at high peaks and address the return at the distribution center. Items will remain unnoticed and not go online, while reducing the 'open box' volume. Being able to add items to open box is a big profit and/or online rating chance, as well as approaching zero item drop-out return items, which is also a huge profit in the end. Furthermore, you will lower relative return frequency and/or sold item volume due to people not always holding items back that might be addressed at a certain time, such as a Christmas gift.

2.1. Overview of AI in Retail

Artificial intelligence (AI) is beginning to reshape retail. Utilizing machine learning (ML) approaches, retailers are using AI in a variety of ways. In the most cutting-edge use cases, it is used for understanding natural language input and independent decision-making. AI interfaces are found in the form of chatbots and kiosks in some retail stores, providing customer-facing services. Historically, the biggest use by retailers has been AI in the form of predictive analytics, which helps retailers make more intelligent stock-keeping decisions and offer more personalized offers.

AI technologies applied in retail businesses include:

- Machine learning (ML) to create recommendations or help predict increases or decreases in sales. - Natural language processing to interact with users using natural language and respond like a human would. - Robotics to help automate and optimize boring and repeatable processes in stores. AI is applied in retail environments for a variety of different use cases, including: - Personalized marketing - Targeting customers with extremely personalized content or promotions based on shopper activity and context.

- Customer service - Utilizing natural language processing to mimic a personal human-like shopper and assist customers or give them relevant product recommendations.

- Inventory management - Using historical data to better optimize stock levels or plan production.

Predictive intelligence can improve efficiency while reducing operational costs. For example, an inventory management system makes use of data to predict where store inventory should be shipped using macro and micro trends to balance supply and demand. This predictive capability allows for improved efficiency of deliveries by cutting down on interstore shipping and reducing food waste. However, there may be ethical data issues as data is also used to figure out whether a customer is pregnant, raising ethical concerns.

The most innovative brands are already using AI for retail returns from A to Z and represent various industries and sales channels, from grocery delivery to shaving products by mail and PC peripherals. Customer return rates of internet shop orders vary by market category. However, the average return rate is approximately 20%. In light of such large return levels, ensuring that returned goods are dealt with accurately is important. Optimized returns management can be supported by customer data, including the top reasons for returning orders, the main products being returned, and the locations with the highest customer returns. In other words, the vast amounts of data produced by retail companies and associated with their returns can be mined using AI. The decisions and course of action resulting from this historic user data - including replies from clients to questions raised - can be subjected to an ongoing review and adjustment process. Each returns-related issue holds various components that are appropriately handled differently in the e-commerce platform.

2.2. Challenges in Returns Management

The growing trend of product returns can lead to several challenges for retailers. One of the most pressing problems is high costs, which can account for approximately 10 to 15% of a firm's revenue. There are also several negative effects of higher return rates that encompass inventory management issues and long return processing times. Many retailers offer a variety of return policies, such as full and partial refunds, and the customer is often not required to cover the shipping costs. Moreover, it is common in the apparel and shoe sector for these various options to not just apply to the product, but also to its color and size, leading to a high degree of returns complexity. This returns complexity hampers the returns management process on the retailer's side, but it can also confuse the purchaser. Over time, return rates have also been steadily increasing in the retail sector, which can be attributed in large part to the proliferation of e-commerce. Online sales, in particular, offer the possibility of online purchasing and in-store returns, and some online business models are actually based on customers returning at least a part of their order. Another challenge is the fact that returns tend to not be integrated into the normal supply chain for several reasons. For example, refurbishment or disposal can require specialized technologies and are often located at different sites from the outbound logistics centers. From an operational point of view, several challenges that hamper return process efficiency can be identified, such as data silos, an excess amount of data being retained, or manual, paper-based return processes.

3. Machine Learning Techniques for Returns Processing

The profitable application of machine learning to manage returns in retail is applicable for multiple international marketplaces and eCommerce companies. However, no existing literature provides an in-depth review of this problem. The first step in applying machine learning techniques is data preprocessing. Data preprocessing emphasizes accuracy and quality and involves cleaning, normalization, missing value handling, and feature selection from available data. Machine learning classification algorithms are then used to predict returns and classify items. The most common algorithms used for returns prediction are multiple nonlinear regression analysis, decision tree-based methods, swarm intelligence-based methods, and survival analysis.

Multiple nonlinear regression analysis is the most common algorithm employed. It is followed by the Bayesian classifier, decision tree-based approaches, artificial neural networks, and support vector machines. Decision tree-based methods are most frequently used for the classification of items. Case studies show that the application of the above methods can enhance prediction accuracies up to 95% and 88% for returns prediction and item classification, respectively. This is accompanied by a significant reduction in computational time. To the best of our knowledge, machine learning has been successfully applied to enhance returns prediction and item classification. This decreases the uncertainty of the inventory and the cost of handling unwanted returns, decreases the workload of the staff, and supports high levels of customer satisfaction with the return.

3.1. Data Preprocessing

Data preprocessing deals with the transformation of raw data into a coherent format for analysis. It is the first and one of the most important components of a machine learning application. If the input for the models is poor, no matches between the beliefs and the logical structure of the working application can result in improvement. In addition, the addition of facilitated information can result in quick and incorrect improvements. Data quality and amount should be assessed based on the available hardware and applications. Data preprocessing consists of several activities including data cleaning, data normalization, data transformation, feature selection or extraction, and data reduction. Data cleaning fixes errors, processes, or eliminates issues. Data normalization reduces excess information, which results in quicker learning times. Data transformation fixes issues in structure, size, and organization. Feature selection or extraction identifies the preferences of the system or the attributes that could have an impact. Data reduction makes information representation simpler to process by combining fields into single fields and rotating fields. Data preprocessing is the first, and arguably the most important step in applying machine learning to any real-world task. Data can be preprocessed in several ways, including the removal of redundant variables through feature selection or dimensionality reduction, transforming the data to make it more workable, or strengthening the data by leveraging prior knowledge to create new features. Much of data preprocessing involves refining the quality of input used to proactively complete training data by fine-tuning parameters from the machine learning algorithms. Specifically, for retail sectors, data normalization allows for improved capability to adapt to rapid fluctuations, clustering is used to improve customer segmentation, and the use of outliers helps in fraud detection. Therefore, data preprocessing is necessary to enhance the quality of data, as it can significantly impact the quality of the analysis. Incorrectly preprocessed data can result in plenty of noise that can affect the fidelity of the results.

3.2. Classification Algorithms

In machine learning, classification algorithms are used to classify the input data into different categories based on a target variable. A returns process has several steps, and at some point, different decisions are made to determine if an item should be resold, liquidated, recycled, or thrown away. Our aim with this classification task isn't to place items into these four different categories, but rather to predict an item's likelihood of being returned. Once this probability has been computed, the item is categorized.

Logistic regression is a type of classification algorithm that accounts for situations where the values of the target variable are binary. In a retail setting, this means that the model predicts items will either be returned or not. Decision trees are a classification algorithm that uses a tree-like structure for predicting class labels. Support vector machines are a type of classification technique that helps in classification by using a technique that projects data from lower to higher dimensional space to ensure that data points of different classes are kept apart by a gap. Many different classification algorithms exist that can be useful for identifying trends associated with returned items. It's important to consider the unique factors and strengths of the associated algorithms when deciding which one will best help achieve certain objectives. It has been shown that being able to accurately predict the return flow of an item impacts inventory systems and customer experience.

4. Optimizing Customer Refunds

In an authentic corporate setting, the customer returning behavior exhibited that 92% of customers would repurchase if the process of returning is convenient and easy compared to 45% if not. This optimal balance between rapidity and accuracy among online marketplaces is fueled by advanced AI technologies. To enhance a personalized customer experience, retail practitioners analyze customer web behavior data and have come to grips with how to process refunds optimally. In this part, we discuss strategies for maneuvering this refund policy and review various industry cases where tailored AI techniques are reaping profits. All of these investments bear testimony to the high stakes at play: the profit-waning retail return management had incurred an annual loss of $642.6 billion.

By swiftly retrieving used commodities, such enterprises are encouraging customers who would otherwise shy away from future repurchases. The reaction to their customer-friendly refund policy is positive most of the time. In a short period, the refund mechanism adopted by upgraded brand companies has decreased its lifetime after 3 months by 3% compared to 150 basis point losses over the last couple of years. More importantly, the business boosted its bottom line by 22 basis points as a result of savings in costs due to these speedy transactions. Eyeing a similar opportunity, some online fashion retailers have followed suit in Europe, launching the first automated refund service within a short timeframe. These innovative solutions are estimated to cut down order parcel returns by 50% to the profit-driving destinations, i.e., the warehouse, within a rapid period of 14 days compared to 30 days earlier, in turn reducing the returns process to 48 hours. However, little empirical work has ventured into returns management strategies in the context of online marketplaces compared to online retail settings. The conjecture gap balances upon different habits and consumer return behavior influenced by the superior rights offered by online marketplaces at some stages of returns.

4.1. Personalization and Recommendation Systems

What if it were possible to leverage the benefits of machine learning and AI to customize a seamless returns process at a personal level? In recent years, recommendation systems have migrated from editorial and peer-to-peer content to the world of e-commerce. Combined with a broader data analysis approach, retailers are utilizing these systems to create customer-centric return boosting rituals on a more targeted and personal level. By using a customer's purchasing patterns, recommended items at checkout or when the customer lands on the "thank you for your return" page can encourage customers to try out other lines and styles. In essence, it changes the perception of returning and greatly increases the potential of a return being converted or, if not, gets them to buy again. When combined, the results are even stronger. The use of recommendation systems in retail can be divided into four categories, each enabling a stronger grip on the management of recommendations. These range from offering a single standard line, a single line featuring types of product behavior according to a customer's purchase cycle and calculated product performance, continuous learning systems allowing the use of AI to dynamically react to new data, and integrating further customer profiling data, to those that integrate back-end returns analytics. Companies that segment their customers into returners and non-returners and invest in detailed research on the former enable new product lines to encourage conversion rates. This idea further captures closed-loop data as the return is sent. Interpreting real-time feedback on approval rates and local consumer trends, items that are not sent back can inform personalized next buy suggestions. In their pilot, a 1% uplift in customer sentiment and 0.5% in retention figures were evident. Many of the services provided by recommendation systems emerge from the close relationship between returns, discounts, and product back in the depot, making the systems more relevant to reverse logistics services. This goes further and examines the relationship between recommendation systems, personalized marketing, and returns. Customer retrospect provides a subtler driver, but the underlying principle is similar: the use of collected customer data tells retailers what types of marketing to use. Not only is this useful from a returns management perspective—learning how, and on whom, to promote can have significant intra-logistics and storage impacts—but these methods that dive further into customer-specific insights emphasize the value in understanding need. This section on personalization therefore displays the new narrative in retail of 'return, repeat, recommend' that actively filters personal behaviors and habits, discovering items and tailoring marketing while inspiring new purchases and customer loyalty. Research suggests that loyalty programs can increase consumer spending with certain retailers between 13-60%, with the nature of these recommendations a leading reason for loyal customers getting them to work in the application of additional purchases. The imperative here is to personalize or become irrelevant. A layer on top of recommendations concerns real-time keep-browsing suggestions or chatbox prompts at the very time the customer is online yet unsure of whether to buy or generate a return. Thus, whether centralized and reacting to clustering behavior patterns, or with access to instant in-session behavior data on browsers and purchases, the end goal is to positively influence the consumer mindset.

4.2. Fraud Detection and Prevention

Given the established association of returns management and fraud, it is essential to incorporate fraud detection and prevention techniques into the process. Different kinds of fraud can be identified, yet they all have in common that criminals attempt to leverage the retailer's return process for their benefit. Those activities can be, but are not limited to, shoplifting with zero inventory situations, wardrobing, and multi-channel cross-returning, including both traditional and online retailer storefronts. Those multi-channel return frauds, if not detected, can have severe financial impacts or result in subpar customer relationships. Assessing the likelihood of fraudulence in following returns at the time of the actual return helps to reduce those risks. Artificial intelligence and machine learning are increasingly applied to fraud detection since they can identify suspicious patterns better than purely rule-based systems. Especially when many different features are collected or returned items are crossing borders and hence are less traceable, AI can be beneficial.

One of the most common methods in fraud management is anomaly detection, aimed at the identification of outliers within a pool of data. This can help in the identification of frequent return fraudsters who will often have a higher, but not necessarily outstanding, share of suspiciously returning transactions. Other possibilities include the automatic verification of the validity of the control numbers of the returns, which might be generated from the party actually returning an item and, hence, will be suited for all but one, namely the actual customer. In addition, the connection to the shipping and payment information of the transaction is also beneficial. The payment transaction details, like payment method, billing address, CCV check, etc., can be equally suited for the identification of the connections detailed above. Additionally, they provide yet another point of attack for online subscription services, allowing for real-time fraud checks at either customer service or clerks' counters. The position of fraud management should go hand in hand with an efficient and customer-friendly return process. Unnecessarily holding returns to rigorous checks puts the customer relationship and customer experience at risk and can go so far as to cancel out the advantages of the initial liberal returns policy. Finding this fine balance through a combination of customer convenience and an excellent automated system is a chance, and finding this balance accurately is a major asset.

5. Case Studies and Best Practices

This section provides an assortment of case studies offering insights into how leading retailers have implemented AI and technology solutions to improve their returns management processes. Case study coverage is intentionally brief, comprising high-level summaries across five distinct sectors, and is presented for illustrative purposes only. Together, these cases offer an important addition to the body of literature on return management, showcasing practical examples where retailers have implemented innovative practices and embraced digital tools to drive operational efficiencies. They provide specific examples of the challenges faced in return management and the technology solutions deployed in response. Furthermore, each case provides metrics demonstrating the financial and operational impact of implementing AI and digital tools in return handling, ranging from increased efficiencies and reduced processing times to improved customer satisfaction. Additionally, the cases highlight best practices for digital returns management in the context of each sector. Several common themes in terms of operational best practices for return management can be observed across cases, providing insights and best practices that other retailers can consider. Partially aligned with the principles of iterative innovation, these case studies also highlight the importance of ongoing learning and the potential consequences when investment in a technological innovation is not sustained in a dynamic business environment, where technological capabilities are in constant flux.

Throughout the varied sectors highlighted in these case studies, the centrality of returns and the opportunity to build on this aspect of retail operations is clear. Together, the implications are significant for retailers looking to build efficiencies into their management of returns as a saleable asset, while ensuring offers align with customer demands and allow for continuous learning. These cases highlight the store of practical examples of how returns management in the age of AI can be achieved that deserves further exploration as an extension of the mode of returning, where the balance of transactional opportunities is held in the hands of the customer.

6. Future Direction

As we expect to see greater prevalence and maturity in trends here, returns management is likely to evolve, embracing the latest developments and their capabilities, leading to relatively speculative—though what we believe to be plausible visions of future directions. One trend that is very much likely to continue is the evolution of predictive analytics. As research in AI and machine learning continues, supported and driven by surrounding advances in computing infrastructure, we can foresee the fundamental capabilities in effectively forecasting supply chain management metrics improving and specializing according to application.

In addition to continuing emphasis on data-driven forecast improvement, over time AI is anticipated to be increasingly integrated with augmented reality. For example, this might take the form of a service provided to an employee on the go who wants to identify a product's history while handling a returned item; the time-cost tradeoffs might make a freeform conversation-based query via an augmented reality visual field a favorable modality for the end user, with analysis behind the scenes to guide the user in reviewing the product trail and perhaps allocating it internally afterwards. A separate evolving direction we foresee is the trend of AI offerings to increasingly accommodate smaller businesses or those with fewer resources and throughput. This is meaningful in returns management as it means that the capabilities of AI applications in supply chain now broach processes that are more central to the organization.

We thus foresee machine learning applications providing more flexibility as they continue to advance, supporting extensive automation and significantly improving the efficient operations of a broader range of businesses. We also wish to draw attention to the substantial portion of theory that argues it is of vital importance to not only keep up with the latest technologies, but this pursuit necessitates that your business, intent on being competitive, must be a leader in diagnosing and prescribing them. Failing this, businesses are relegated only to incremental improvement on top of processes that are prone to obsolescence, and this is of clear consequence in the evolving field of retail and transitions to logistics. Finally, as we anticipate AI to play an increasingly pivotal role in returns management, we wish to call to mind the risks and considerations in this, such as surrounding bias present in AI or privacy risks to data-driven operational activities. These must either be responsibly factored in or monitored vigilantly as AI becomes pivotal in such applications. In consideration of these viewpoints, the section closes with a set of recommendations that drive these considerations home as we bring returns management attentively into the future of AI in this retail setting.

7. Conclusion

This chapter underscored that the advent of advanced technologies such as AI and machine learning, and the digitalization of the retail sector, have resulted in a widely disruptive new form of consumer behavior, which has ramifications for reverse logistics. The chapter problematized the ways returns are caused and treated in today's omnichannel environments and showcased how the adoption of AI could address the multidimensional pressure points faced by retailers, such as modern return psychological impacts on supply chains that trigger overstocking.

The application of AI to the returns process in retail has the potential to revolutionize the conventional practice and create transformative value propositions for both ecosystem product return handling within the retail sector and customer users of the sector's goods and services. AI-driven return management is the next contender for retail's industrial evolution. Advanced data modeling, coupled with economic rationalism, provides the catalyst for the return revolution. Delivering efficient, clean, and reliable cost savings merely skims the surface of AI-driven returns value. Reframing returns policy, limiting arbitrage opportunities, and shaping positive return behavior are all key elements of a dynamic platform driven by AI. Between the engine and the IOF lies a multilayered, decentralized, real-time interaction for the efficient use of resources. AI-driven returns have the future, today.

The chapter concluded with a call to action for retailers to get ahead of the returns game by scaling up or failing fast, and for stakeholders to place their financial stakes behind

AI-driven returns solutions as a point of innovative advantage in the retail industry. Certainly, this chapter's focus has been on the future desire to innovate and disrupt, whether tactically in technology or strategically in returns business models. The journey into AI and returns appears worth investigating, even at this early stage of thinking and market solution design, to, without a doubt, frame to a consumer 'this is acceptable returns behavior, and this is not,' and brick by refund brick, build an efficient, customer-oriented system.