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Product Return Prediction in E-Commerce Platforms

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Abstract
Online shopping is fast and easy,but returning items is just as easy, and that's becoming a big problem for online stores. Every return wastes time, money, and effort. This project brings together smart ideas from recent research to build a system that can predict returns even before a customer places an order. Many systems already use things like past purchases, product details, or customer reviews to guess return chances. But we're adding something new: Digital Touch Latency (DTL) a way to track how long a shopper hesitates, like checking the size chart or switching colors. These small actions often mean the customer is unsure, and unsure customers are more likely to return things.We're also using a Sentiment Drift Engine to watch how product reviews change over time. If people start giving worse reviews suddenly, our system notices and increases the return risk right away. By combining hesitation behavior (DTL), review trends, and regular shopping data, our machine learning model can make much better predictions. This helps stores act early by showing better recommendations, fixing product info, or warning about risky products.In short, fewer returns help stores spend less and keep customers happy with their shopping.

Keywords: *E-commerce returns prediction,Return reduction strategies,Behavioral analytics in e-commerce,Machine learning for returns prediction,Real-time return prediction,Postpurchase return prediction.*

1. Introduction
Online shopping has revolutionized how people shop—it's fast, easy, and available a all hours. However, with convenience comes a newer difficulty e-commerce sites face: product returns. Each times a customer return something, it costs the store time, money, and resources. To combat this issue, researchers have used different means to understand past orders and predict when a product might be returned leveraging the proverbial plethora of data available such as previous purchases, product offerings, and customers reviews. In this literature review, I will review areas of study into existing return prediction systems. Specifically, I will look at what types of data have been used including customer behavior, product affordance and product reviews to estimate return risk. I will identify gaps in existing work and highlight newer concepts like Digital Touch Latency (DTL) and Sentiment Drift, as distinct ways of considering customer hesitation and shifting opinions. Understanding what we already know allows us to build on that knowledge through more sophisticated systems that better predict customer returns and improve shopping experiences.

2. Related Works and Background
E-commerce platforms face frequent product returns, which increase costs and affect customer satisfaction. Predicting returns early helps reduce these issues and improves decision-making. This work focuses on identifying early indicators of return by analyzing user behavior and review patterns. Farber and Guy (2022) analyze customers' return reasons in e-commerce: wrong fit, product defects, or change of mind [1]. The researchers look at the product detail (name, description, price, category) for patterns; for

example, clothing is almost solely returned because of fit, and electronics are mainly returned due to defects. If retailers understand returns reasons, they can help develop better products or price products accurately; they can also provide the right fit (if clothing) to minimize returns. Rajasekaran and Priyadarshini (2021) develop a framework for predicting the risk of product returns that aim to avoid costly returns in e-commerce by using customer product reviews, product IDs, and transaction time to determine a return risk level based on five levels for sellers to get gain an idea on various product's level of return risk from very low to extreme [2]. It also uses machine learning (namely regression, optimization, and Gradient Boosting to produce the best risk estimates) so that the sellers can act early on these returns, to prevent returns or overall reduce losses. The results indicated that both customer product reviews and customer return history were strong predictors of return risk and the authors suggest in future research modeling using the same constructs but that now also explore text-based customer feedback and methods to reduce costs as well. Hou and Yang (2016) examine how customers and companies co-create value on social e-commerce platforms and identify that these platforms combine shopping with sharing experience and helping others [3]. Findings show that good usability, security, and organisation enable participation and that users are more motivated by kindness rather than reward mechanisms, e.g. discounts, points. User behaviour, whether consumer behaviour or participation behaviour changes over time, and retailers must develop effective strategies to influence retrieval behaviour. To what extent the users navigate and participate on a platform is a function of perceived experiences, and when the user has a positive or helpful experience, also the perceived community of practice. Zikopoulos (2025) investigates the" defective allowance" policy, in which customers receive a small discount to accept deceptively non-defective merchandise (i.e., a minor defect; damaged) [4]. The study used models to establish how many factors (e.g., price, repair costs, and customer demographics) relate to the size of the discount. The findings showed that product price is more important than the replacement cost in deciding size of the discount. The approach has the potential to limit returns, cut processing costs, and limit waste. Zhu and Deshpande discuss the increasing issue of product returns in online shopping by proposing the use of HyGraph, a graph-based model that indicates relationships between customer, purchase, return and product similarity [5]. The authors also proposed LoGraph, a faster analytic methodology that only examines the relevant portions of the graph, enabling it to work with larger datasets. The authors evaluated LoGraph against data from a fashion store and it outperformed all other return prediction methods, allowing ultimate retailers to take operation decisions sooner to reduce returns and improve the customer experience. Li et al (2018) introduces HyperGo, a graph-based approach to predicting product return at" Point of Purchase" (PoP). HyperGo links items in the cart to items purchased and developments patterns, such as customers selecting multiple versions of an item, and establishes two levels of risk to receive a product return predictive score - the basket level and item level [6]. HyperGo yielded improvement over predictive methods noted in earlier studies using data from fashion retailers, and can facilitate early methods of intervention for retailers, such as better fit suggestions, to minimize product returns and enhance a consumer's online shopping experience. Tuylu developed a model to predict product returns in the fashion industry using ensemble machine learning methods, particularly Stacking and Voting methods. The authors collected real data from a global clothing brand to observe the return activity of women's trousers across hundreds of stores [7]. The model was able to predict results based on inputs such as seasonal details in terms of color, price, design, and store.The biggest benefit was the Stacking algorithm was the most accurate at 86 percentage and old methods predicted only about 70 percentage. There cost savings by predicting returns with accuracy were reduced storage, reduced shipping, and reduced return costs. This study demonstrates how machine learning can assist companies in obtaining a more accurate prediction of returns allowing them to minimize waste and guiding improved decision making in production, sales, and supply chain

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planning. It also proposes that similar methods be transferred to other sectors as well. Lin et al [8] researched the reasons for product returns in China after shopping online. Through Structural Equation Modeling (SEM), the authors were able to determine the effects of service, delivery, price, product, return policies, and customer feelings on returns. Responses were gathered from younger shoppers in Shanghai and Hong Kong. Their findings found that the greatest reason for returning a product was the consumers' intention to return the product, which was highly related to an easy return process. Additional reasons connected to returning a product include poor delivery, reduced product quality, and low customer satisfaction. Additionally, the authors learned that customers, even when satisfied, may be keener to return any products with easy return options. The authors concluded with a recommendation that online retailers included improved return policies, enhanced delivery processes, and to provide accurate descriptions about product information to reduce return rates and follow-up customer satisfaction. Griffis et al [9] examined how returns influence customer's future purchasing behavior with online retailers. While returns almost always seem like a loss for the seller, this study showed the opposite; that if the return is seamless and quick it has a great chance of having customers shop more later on. The researchers used an online retailer's actual data and compared shoppers who completed an online return to those who didn't. They found that customers that reported a satisfactory return experience were more likely to return, spend more, and purchase more items. They also found that customers who got their refunds quickly were much more satisfied. Ultimately, the crux of the report is that a good return policy creates trust and loyalty - companies must adopt a new way to look at their return related costs and think of returns as an opportunity to retain a customer, not solely a loss. Ho and Le [10] present a new technique for grouping and analyzing customers by merging their shopping behavior with their personal attributes like their age, gender, and location. The researchers modified the RFM model (Recency, Frequency, and Monetary value) injecting demographic data to develop the RFMD model. An empirical study conducted in this paper used actual online sales data and utilized machine learning models (K-Means and K-Prototypes) to separate customers into five groups. The findings indicated that demographic data can further characterize customer groups, which could improve how companies define their customer targets, as well as allocate resources into focused marketing strategies, saving costs and better informing business decisions. Lian and Yen [11] included a study that examines differences among online shoppers rather than treating them as one group. By way of surveys and stimuli, they identified four different types of shoppers—Shopping Lovers, Direct Purchasers, Suspicious Browsers, and Incompetent Consumers—each having their own habits, attitudes, preferences, and concerns. They further analyzed how ease of use, enjoyment, security, and social pressure influenced the association between shopper attitudes and purchase intention, revealing that favorable attitudes lead to greater purchase intention. The authors concluded that as a result, sellers can apply these insights to help in designing their marketing and selling effort to meet each shopper type. Kedi and Borar [12] presenting an AI-based online fashion shopping system that predicts whether customers will return garments before the purchase order is placed. The system uses deep neural network(s) to analyze the size of the customer, shopping behavior and their choices at checkout, as well as product features and previous return data. The system runs real-time at check out and empowers retailer to lowered returns by altering delivery costs, sending coupons, or making the items not returnable. The result was the lowering of returns, less costs, and higher levels of satisfaction with the customer. Heilig and Lessmann [13] describe a smart system for online fashion retailers that uses ensemble learning to determine which products will most likely be returned. In the research's initial analysis of real data from a retailer, their ensemble model was found to make superior predictions over simpler methods but was struggling to compute with big data. The authors developed a cloud-based architecture that allows for independent processing of components and real-time updates based upon changing customer behavior. The cloud-

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based architecture helps retailers determine what purchases are at high risk of return, provide better alternatives, as well as minimize the costs associated with returns. The case illustrates additional value for cloud-based machine learning for return management. Pourshahid defines trust within online shopping as an issue since usually, the seller and buyer do not know each other [14]. Therefore, the author explains a personal trust model that looks at the user's personal priorities (speed, secure, fair price, honesty) instead of all users learning the same general practice about trust. The authors then utilize graphical representations (GRL and UCM) to characterize how consumers expect trust on their online shopping. Subsequently, the authors explain that trust depends on individual criteria which means it should not be generalized. Thus, it will lead to safer buyerseller decision- making, and better design and understand more flexible types of trust systems that allow for both different platforms and users. Hernandez aims to formally quantify user interaction on ecommerce websites and suggests the use of model checking with temporal logic to formulate a multi-dimensional account of browsing behaviour. Server log files can be translated into a sequence of events, which will capture all visited pages as well as the permutations of that event, rather than simply a count of the pages visited [15]. The proposed method is evaluated on a Spanish webstore called Up and Scrap, and it reveals patterns for individual page-level visitations, prepurchase views, and non-purchase behaviour in context. This technique provides deeper interpretation than a simple link analysis, and the findings can help store owners redesign aspects of their websites in order to increase their sales. Hsiao discusses the conceptualizing effects of product quality, price, and customer service on an e-commerce return policy. Differentiating itself as an academic paper, it opens by noting that online consumer behavior is characterized by greater uncertainty and that some customized return policies can mitigate unnecessary returns. Next, it describes its findings regarding all three antecedents of return policy [16]. Importantly, there is not always a reasonably linear relationship between e-commerce return policy and its antecedents. For example, having a lenient return policy does not always mean that e-commerce return item is high quality. Low quality goods may have a high return to buyer refund ratio, and jobs where the seller is improving what is already good goods yields negligible benefit (low risk) when having high refunds. The study mentioned examples where sellers would not assume returns on all goods due to too high return costs, and one case of return burden. The data provided some tangible guidance for successively matching return policy, product quality, and price to risky customer expectations as well as the profitability space. Ninh describes how customer feedback and vendor interaction can influence in a seller's e-commerce sales and uses market data from Vietnam Shopee to illustrate this influence. Clearly, customer engagement through answers, thankyous and interaction leads to increased sales, though stronger increases in e-commerce order levels were evident when communicating about home lifestyle products – the baseline sales levels increased 1.4 times. For products in categories such as beauty and fashion strong levels of product quality and marketing created a strong selling performance. Overall, the findings clearly show that the use and effectiveness of positive feedback and seller interaction will lead to trust, satisfaction and ultimately successful sales to help the seller identify effective plans and buyer relationships in competitive societies from an online perspective [17]. These immense markets indicate new ways for sellers to use customer feedback and seller interaction to differentiate themselves. Gajewska considers the influence of service quality on customer satisfaction in e-commerce by employing the SERVQUAL model approach with a survey of Polish young shoppers. The assessment involved five service quality dimensions comprising reactivity, reliability, safety, empathy and physical features. This study found reliability to be one of the most important, with punctual and prompt updates being valued the highest by survey respondents. Overall satisfaction with service quality remained high; however, gaps still existed in delivery and online communication [18]. The article concludes that e-commerce firms should focus on improving levels of trust, rapidness, and accuracy in the delivery

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of service quality in order to increase satisfaction, loyalty and competitiveness, while recommending to e-commerce firms to measure and enhance service quality on a regular basis. Hendriksen predict whether a customer will purchase on an e-commerce site, distinguishing between logged-in shoppers and anonymous shoppers. The study considered four weeks of actual shopping behaviour data and variables such as session time, device type, number of pages viewed, and purchase history for logged-in users (logged-in users do account for a larger proportion of purchases). The results built separate models for each distinct group under analysis [19]. The logged-in model was the highest to predict purchase behaviour, while the anonymous model performed more than 17 percentages better than the company's current process under investigation. This suggests it is possible to predict if a customer is likely to purchase, without user identity and has implications for retailers in an online shopping environment. Rajasekaran tries to tackle the issue of product returns in e-commerce, at a time when this growing problem has reached critical mass, by utilizing customer reviews, ratings, and buying patterns, predicting when a product will be returned. Although previous research described CNN or LSTM models utilized candidates of the same data, CNN or LSTM have trade-offs - and are good at different things. CNN are great at capturing local patterns, while LSTM better handle the longterm meaning of text [20]. Here, the authors draw both theories together, building a hybrid CNN-LSTM model. The model was trained on 34,000 Amazon reviews, after cleaning the text, doing feature selection, and sentiment scoring. The CNN saves words, while the LSTM builds understanding based on sequence. The Adam optimizer improved performance. This hybrid outperformed others tested, with an accuracy up to 97.67 percentage, making it useful for identifying returns right away, before they happen. MZetterberg investigates high return rates of products in e-commerce, which can negatively affect profitability and efficiency. While previous studies used Convolutional Neural Networks (CNNs) or Long Short-Term Memory (LSTM) networks on their own - CNNs to identify patterns and LSTMs to understand sequences - each approach has limitations. The researchers create a hybrid CNN-LSTM methodology, which is trained using 34,000 cleaned and prepared Amazon reviews (containing a rating, text and sentiment) using Word2Vec, the Adam optimizer and using 10-fold cross-validation. CNNs allow the delivery of the most important words in percent form and LSTMs allow the delivery of the context of product return, which collectively provide a higher performance than using CNNs or LSTMs on their own, with a reported accuracy of 97.67 percentage [21]. This methodology attempts to establish a process to predict returns earlier in the process funnel, in an effort to manage costs and enhance customer satisfaction levels.

3. Proposed Methodology

The proposed system is intended to predict product returns for an e-commerce site by combining data on customer profiles, aspects of products, transactional data, behavioral patterns, and customer reviews. The methodology is designed sequentially from the stage of creating the data set to the implementation stage, to assure technical rigors and business relevance. This structured approach enables the model to learn meaningful patterns and generate accurate return predictions. his ensures better prediction accuracy and practical usability.

Dataset

The dataset is designed to reflect transactions in a real world e-commerce setting and spans multiple dimensions. The dimensions of customer data feature demographic characteristics, purchase frequency, loyalty status, and a history of previous returns. Product-level characteristics including product category, brand, size, price, and ratio of historical returns are included to effectively capture item-level behavior. Transaction-level features related to the shopping cart include cart size, order time stamp, payment choice, discounts applied, and city of delivery, among others. Behavioral features were also captured, particularly Digital Touch Latency (DTL) which measures hesitation during user behavior, such as switching product variants, checking size charts, or pausing the checkout process. Additionally, review data (both rating and text reviews) is accessible, with sentiment drift being mined from the reviews, in

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order to obtain insight into changing customer opinions of products over time Shown in Figure 1 and 2.

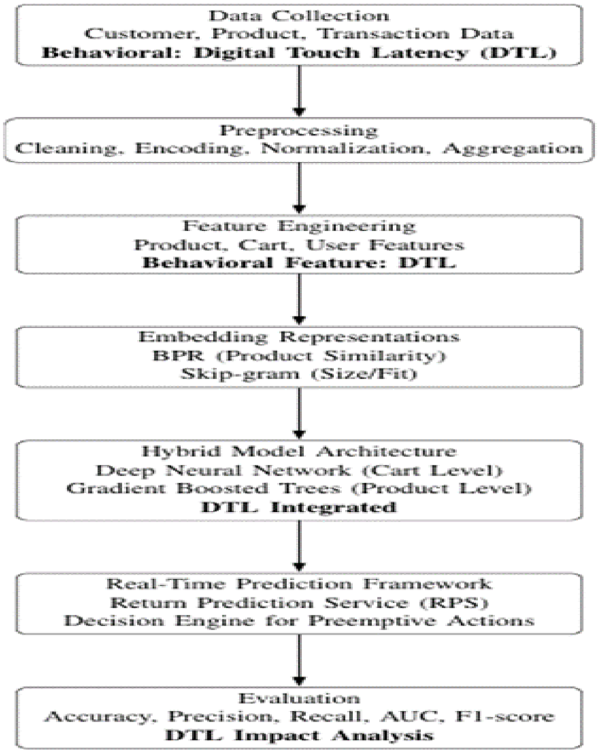

Figure 1 **Pipeline of the Proposed Product Return Prediction System with Digital Touch Latency (DTL)**

1	session_id	user_id	product_ic	time_spen	variant_sw	review_te:	sentiment_	is_returned
2	1	39	103	73	2	Loved it!	0.873916	0
3	2	52	118	207	0	Not worth	0.107604	0
4	3	29	102	69	2	Damaged i	-0.38895	1
5	4	15	118	108	2	Size misma	-0.20604	1
6	5	43	119	120	3	Size misma	-0.10559	1
7	6	8	106	109	1	Size misma	0.201189	0
8	7	21	119	33	1	Good qual	0.031359	0
9	8	39	108	15	1	Good qual	0.838784	0
10	9	58	100	30	0	Perfect fit	-0.00607	0
11	10	19	107	133	1	Perfect fit	0.984316	0
12	11	23	106	9	1	Loved it!	0.70285	0
13	12	11	117	43	1	Not worth	-0.58298	1
14	13	11	107	15	3	Worst pro	0.86119	0
15	14	24	100	52	4	Worst pro	-0.76727	1
16	15	53	110	119	0	Damaged i	0.634899	0

Figure 2 **Sample Screenshot of the Dataset Used in the System**

4. Detailed Methodology

4.1. Preprocessing

Initial data processing focused on cleaning and preparing the dataset for modeling. Missing values were handled using statistical imputation techniques. Categorical variables such as product category, brand, and payment type were converted into numerical form, while continuous variables like price, browsing time, and DTL were normalized to maintain a consistent scale. Review text was cleaned, tokenized, and converted into sentiment scores to support sentiment drift analysis. These preprocessing steps resulted in a structured dataset ready for feature engineering and model training. This ensures consistent data quality and improves the overall performance of the prediction model.

4.2. Feature Engineering

To better predict performance, features are engineered at multiple levels. At the product level, features include category, brand, size, and historical return ratio. Cart-level features include cart size, order diversity, discounts used, and delivery location. User-level features include purchase count, loyalty status, and returns frequency. Behavioral features include browsing time, number of product views, and DTL, serving as signals of hesitation. Review-based features include sentiment scores and sentiment drift, accounting for changes in customer perceptions of the product over time. The purpose of engineered features is to better represent the true multi dimensionality of a return behavior.

4.3. Embedding Representations

Embedding techniques are used to represent relationships that are more complex than hand-crafted features. One way to generate product embeddings is to employ matrix factorization methods, for example, Bayesian Personalized Ranking (BPR), which can capture similarities across items. Customer embed dings portray shopping preferences and size tendencies for each customer. Text embeddings are obtained from customer reviews, using Word2Vec or transformer-based encoders that allow the system to learn semantic structure from the text data. These embeddings increase representation space, and provide the model with the ability to generalize across different product and customer behaviors.

4.4. Model Architecture

The architecture combines a Deep Neural Network (DNN) for cart-level return prediction using behavioral features like Digital Touch Latency (DTL), and Gradient Boosting (GBM) for item-level risk scoring. Sentiment drift from reviews fur them refines the prediction, improving overall accuracy Shown in Figure 3.

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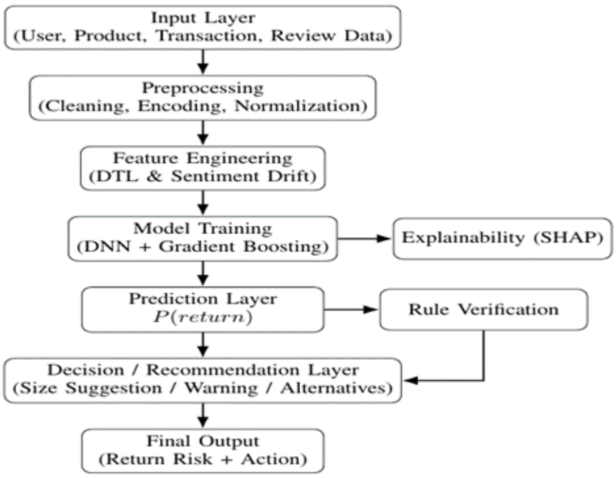

Figure 3 System Architecture of the Proposed Model It Processes Raw Data Extracts DTL and Sentiment Drift Features Trains the Model Applies Explain ability and Rule Verification and Generates Return Risk Prediction with Actions

4.5. Real-Time Prediction Framework

The system operates as a Return Prediction Service (RPS) incorporated into an e-commerce platform. At checkout, po tential returns are processed through the model of histori cal features and real-time features, which includes browsing behavior and DTL, to develop return probability scores in milliseconds. The probability scores are used by a Deci sion Engine to inform actions, including personalized sizing recommendations, alternative product recommendations, or logistics changes based on risk identified. This method allows companies to address potential returns before they happen.

4.6. Evaluation

The proposed system is assessed for effectiveness using both technical and business measures. Technical evaluation utilizes standard measures which include accuracy, precision, recall, F1-score, and ROC-AUC. To explore the value of novel features like DTL and sentiment drift, ablation studies review the impact of omitting each of those features on performance. Evaluation of the business side focuses on spending, percentage return reduction rates, customer retention, and customer satisfaction. This two-front evaluation demonstrates that the system is not only technically sound but also practically useful for e-commerce operations. The proposed model predicts the likelihood of product returns in e-commerce by using Digital Touch Latency (DTL) and sentiment analysis. By observing user interaction delays and changes in customer review sentiment, the system can identify products with a high chance of being returned and suggest actions to reduce returns. This approach can improve customer satisfaction and help minimize return-related costs when implemented with real data.

Conclusion

Numerous studies show product returns are a big problem for e-commerce because they impact margins, increase work load, and sometimes spoil relationships. Most research has focused on aspects of returns: predicting who is likely to return an item, the reason for the return, and examining possible mechanisms to prevent the return altogether. The returns problem can be approached in a multitude of ways. This can include using advanced machine learning and clouds or looking to customer behavior, preferences, trust, and feedback. One strategy is to increase or enhance product information, product fit and sizing, and product quality; another policy is to seek better modes of policy or use smart pricing applications. A common thread across these studies is if retailers can begin to really understand, and explain, customer behaviour pre- and post-purchase; and can at least somewhat predict expected outcomes, they can act sooner to lower return rates and, hopefully drive customer loyalty. Ultimately, being successful as a solution is easier when technology, data and the overall customer experience can support each other in addressing the return challenge and making customers happy.s

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