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Leveraging AI and Deep Learning for E-Commerce Customer Segmentation

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ABSTRACT: As e-commerce platforms compete to retain customers, predicting and preventing customer churn remains a critical challenge, particularly among new shoppers. In this paper, leveraging anonymized large-scale transaction records from an e-commerce platform, we develop ClusChurn-EC, a systematic two-step framework for interpretable customer segmentation and churn prediction. The framework first clusters new customers into distinct behavioral segments based on purchasing patterns and engagement metrics. We then design a deep learning pipeline using LSTM networks and an attention mechanism to predict customer churn with minimal initial interaction data, effectively capturing sequential shopping behaviors. By identifying at-risk customer segments, ClusChurn-EC enables businesses to implement targeted retention strategies.

Extensive experiments on real-world anonymized transaction data demonstrate that ClusChurn-EC provides actionable insights into consumer behavior and outperforms traditional machine learning models in churn prediction. The framework is designed as a scalable analytics pipeline, supporting real-time decision-making for retention management. Additionally, it is adaptable to a wide range of e-commerce platforms and online marketplaces, making it a practical and generalizable solution for churn prediction in digital commerce.

KEYWORDS: interpretable model; customer segmentation; churn prediction; deep learning; e-commerce analytics

I. INTRODUCTION

The rapid expansion of e-commerce platforms has intensified market competition, with businesses continuously striving to attract and retain customers. Online shopping has become an integral part of modern commerce, driven by widespread internet accessibility, mobile applications, and personalized shopping experiences. E-commerce businesses range from large-scale marketplaces such as Amazon and eBay to specialized platforms focusing on industries such as fashion, electronics, and groceries. As consumer preferences and behaviors evolve, understanding and predicting customer retention has become increasingly important for business sustainability.

While many businesses invest heavily in customer acquisition through digital advertising and promotional incentives, customer retention has received comparatively less attention from the research community. However, studies indicate that acquiring a new customer is significantly more expensive than retaining an existing one, making churn prediction a critical area of research. Churn in e-commerce refers to the likelihood of a customer disengaging from a platform, either by reducing interactions or ceasing purchases altogether. Predicting churn presents unique challenges due to the diversity in consumer behaviors. Some customers shop frequently, while others make sporadic purchases influenced by discounts, seasonal trends, or personalized recommendations.

Traditional churn prediction methods can be broadly categorized into two approaches. Survey-based methods provide qualitative insights into customer behavior but are labor-intensive and difficult to scale. Data-driven machine learning models, on the other hand, offer scalability but often lack interpretability, making it challenging for businesses to derive actionable insights. Furthermore, many existing churn prediction models rely on static user attributes rather than sequential behavioral patterns, limiting their ability to predict churn early and accurately.

This study introduces ClusChurn-EC, a two-step framework designed to enhance churn prediction in e-commerce platforms by integrating interpretable customer segmentation with deep learning. The framework first clusters customers based on their shopping behaviors using an automated clustering pipeline that incorporates feature engineering and k-means clustering with Silhouette analysis. These segmentation results are then utilized to improve churn prediction through a deep learning model based on Long Short-Term Memory (LSTM) networks and attention



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mechanisms. By capturing sequential purchase and engagement data, the model effectively predicts customer churn with minimal initial behavioral information while maintaining interpretability.

To evaluate the performance of ClusChurn-EC, extensive experiments are conducted using anonymized transaction records from an e-commerce platform. The results demonstrate that the proposed framework outperforms traditional churn prediction methods, providing valuable insights into customer behavior and enabling businesses to implement targeted retention strategies. Unlike existing black-box models, this approach enhances interpretability, allowing e-commerce platforms to proactively address churn risks and improve customer engagement. Additionally, the framework is adaptable to various online business models, including subscription-based services and digital marketplaces, where customer retention plays a crucial role in long-term success.

II. E-COMMERCE CUSTOMER BEHAVIOR ANALYSIS

Understanding customer behavior is essential for developing effective churn prediction and retention strategies in ecommerce. To guide our approach to customer segmentation and churn modeling, we perform an in-depth analysis using publicly available transactional and engagement data from an e-commerce platform. This analysis enables us to identify key behavioral patterns and formulate data-driven strategies for improving customer retention.

2.1 Dataset

We use anonymized transaction records from an e-commerce platform to analyze customer behavior and predict churn. The dataset includes 200,000 new customers who made their first purchase within a two-week period, along with behavioral data from 1 million existing customers. This dataset provides a structured and representative sample of customer engagement patterns, allowing for a detailed examination of shopping behavior, purchase frequency, and retention trends.

Customer activity is categorized into two primary feature groups: transactional behavior and engagement metrics. These features provide insights into how customers interact with the platform, their purchasing habits, and their likelihood of churning. Data is collected over a 14-day period following a customer's first purchase, ensuring a standardized observation window for churn modeling. Table 1 presents the key behavioral features extracted from the dataset, which include purchase activity, browsing behavior, and customer interactions with the platform.

ID	Feature Name	Description	
0	Orders Placed	Number of completed purchases	
1	Cart Abandonment	Number of items added to cart but not purchased	
2	Page Views	Total number of product pages viewed	
3	Time on Site	Total duration spent browsing	
4	Repeat Purchase	Whether the customer made a second purchase within 14 days	
5	Discount Usage	Number of transactions involving promotional discounts	
6	Return Requests	Number of product return requests	
7	Customer Support Interactions	Number of queries submitted to customer service	

Table 1: Key Behavioral Features in E-Commerce Data



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8	Wishlist Activity	Number of products added to wishlist
9	Email Engagement	Open and click-through rates of promotional emails

Beyond individual customer behaviors, we analyze customer-product interactions to better understand engagement patterns and predict churn. Instead of social network-based metrics, we define two key engagement-based properties that capture a customer's relationship with the platform:

- Interaction Volume: The total number of interactions a customer has with the platform, including product views, cart additions, purchases, and reviews. This serves as an indicator of overall engagement.
- Purchase Conversion Rate: The ratio of completed purchases to total interactions, measuring how effectively engagement translates into transactions.

For each customer, we construct a 12-dimensional time series representation consisting of 10 behavioral features (e.g., orders placed, cart abandonment, page views) and 2 engagement-based properties (interaction volume and purchase conversion rate). Each feature is tracked daily over a 14-day observation window, forming a 12×14 matrix. This structured representation enables sequential modeling of customer behavior, which is essential for churn prediction using deep learning techniques.

2.2 Customer Activity Analysis

Analyzing customer activity over time is essential for understanding behavioral patterns and predicting churn in ecommerce. Figure 1(a) illustrates an example of daily measures of user interactions, such as the number of product views per day during the first two weeks after the customer's initial purchase. Each curve represents the engagement pattern of an individual customer. The curves exhibit high variability and burstiness, making it challenging for traditional time series models, such as Hidden Markov Models (HMMs), to effectively capture meaningful trends. To address this challenge, we compute two key parameters: μ , the mean of daily measures, which captures the overall engagement volume, and λ , the lag(1) autocorrelation, which quantifies burstiness in customer activity. These metrics are widely used in time series analysis to summarize dynamic behaviors while reducing noise. Aggregating these measures across customers, as shown in Figure 1(b), helps in identifying distinct behavioral patterns that can be leveraged for customer segmentation and churn prediction.



Figure 1(a) illustrates customer interaction activity over the first two weeks following an initial purchase. The Y-axis is masked to avoid disclosing absolute values. Each curve represents the cumulative number of interactions a customer has with the platform until a given day. The variability in these curves indicates significant differences in customer engagement patterns, with some users maintaining consistent activity while others exhibit sporadic bursts of interaction.



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Figure 1(b) presents the aggregated engagement trends across multiple customers. The curves display varying degrees of steepness and inflection points, reflecting differences in shopping behavior and long-term retention likelihood. Motivated by prior research in user behavior modeling, we apply a sigmoid function to fit each curve, enabling a standardized representation of customer interaction dynamics:

$$y(t) \ = \ \alpha. \frac{1}{1 + e^{-q(t-\varphi)}} + \beta$$

where q controls the steepness of the curve, indicating how quickly a customer reaches peak engagement, and φ represents the inflection point, signifying when engagement stabilizes. These parameters allow us to quantitatively describe engagement patterns, distinguishing between steadily engaged users and those who interact intensely before disengaging.

To effectively model customer behavior for segmentation and churn prediction, we represent each time-series behavioral feature using four key parameters:

- α (Scaling factor): Controls the maximum engagement level a customer can reach. It adjusts the overall amplitude of the function to reflect different customer behaviors.
- B (Baseline engagement offset): Represents the minimum engagement level or an initial offset in customer interaction. This accounts for customers who start with non-zero engagement at t=0
- µ: Mean interaction volume, summarizing overall engagement levels.
- λ : Lag(1) autocorrelation, capturing burstiness and irregularity in customer activity.
- q: Engagement growth rate, controlling the steepness of interaction curves.
- φ: Stabilization point, identifying the critical period when engagement trends level off.

Each customer's behavioral profile is then structured into a 12×4 feature matrix, where 12 behavioral attributes (e.g., product views, purchases, cart abandonment) are each represented by the four derived parameters. This transformation condenses sequential behavioral data into a compact yet informative format, improving the efficiency and interpretability of subsequent clustering and churn prediction models.

Figure 2 shows Main shopping engagement trends captured by sigmoid functions with different customer behavior configurations. The curves represent how different customer segments interact with an e-commerce platform over time, with variations in growth rate (q) and stabilization point (φ).





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2.3 Customer-Product Interaction Network Analysis

Beyond individual customer activity, we analyze how customers interact with products and engage with the broader ecommerce platform. Unlike social networks, where new users form connections with existing users, in e-commerce, new customers establish transactional relationships with a subset of frequently purchased products, merchants, and categories. These relationships help define the structure of the customer-product interaction network, providing insights into customer behavior and churn likelihood. In our dataset, 200,000 new customers interact with a subset of frequently purchased products during their first two weeks. We denote this subset as κ , representing the most commonly purchased or viewed products within this period. We find these κ products particularly interesting, as they account for a significant proportion of total platform transactions. Specifically, interactions among these κ products generate 114 million customer-product links, while interactions between these products and the broader platform result in 478 million total connections. Given that fewer than 700 million total interactions occur across all 1 million customers, this suggests the existence of a highly influential core group of products that drive early-stage customer engagement. Figure 3: Most early customer interactions are concentrated around a core subset of products



Figure 3(a) illustrates the overlap between the core product set and κ , where we define core products as those with the highest number of customer interactions (purchases, views, and reviews). To validate this assumption, we define the core of an e-commerce network as the top-ranking products by engagement volume, motivated by prior studies on marketplace network structures.

Figure 3(b) presents the purchase frequency distribution of κ products, compared with all other products on the platform. Results show that 44% of κ products belong to the top 5% most frequently purchased products, and 67% of them fall within the top 10% of highly engaged items. This confirms that new customer activity is heavily concentrated around a core subset of products, which may play a key role in influencing early-stage customer retention. Since customer interactions with κ products do not fully overlap with the overall product core, this motivates further analysis of how different customer groups interact with these products, and how these patterns influence customer segmentation and churn prediction.

III. INTERPRETABLE CUSTOMER CLUSTERING

Segmenting customers based on their purchasing and engagement patterns is essential for understanding their shopping behaviors and predicting churn in e-commerce. In this section, we explore how new customers interact with different product categories, promotions, and platform features during their initial shopping period. The objective is to develop an interpretable clustering framework that identifies meaningful customer segments based on their behavioral evolution, purchase frequency, and retention trends.

Beyond its direct application in churn prediction, customer clustering provides valuable insights into consumer habits, enabling businesses to enhance targeted marketing campaigns, optimize product recommendations, and improve retention strategies. Understanding distinct customer personas helps tailor promotional offers, predict long-term shopping preferences, and refine engagement strategies. While this study primarily focuses on churn prediction, the



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clustering approach we propose is adaptable to various business intelligence applications, including customer lifetime value estimation and loyalty program optimization.

3.1 Challenges in Customer Clustering

Identifying well-defined customer segments from complex, multi-dimensional shopping behaviors presents several key challenges. Traditional clustering algorithms, such as k-means clustering and principal component analysis (PCA), often struggle with e-commerce data due to its high dimensionality, dynamic nature, and overlapping behavioral patterns. Below, we outline the main difficulties in clustering customers effectively.

1. Discovering Customer Segments Without Predefined Labels

E-commerce customers exhibit highly diverse shopping patterns, making it difficult to apply predefined customer segment labels. Some customers prefer frequent, small purchases, while others make bulk purchases infrequently. Others may shop only during seasonal sales or in response to promotional offers. Unlike supervised learning tasks where labeled data is available, customer clustering must autonomously identify meaningful segments without prior knowledge of the appropriate number of groups or their defining characteristics. The challenge is to design an approach that adapts dynamically to different consumer behaviors across various e-commerce platforms.

2. Managing Correlated Behavioral Data

Customer interactions with an e-commerce platform involve multiple behavioral dimensions, such as browsing patterns, cart activity, purchase frequency, return rates, and discount utilization. Many of these features exhibit correlations—high cart activity might signal purchase intent, whereas frequent returns could indicate customer dissatisfaction. However, correlated behaviors cannot always be treated as identical. For instance, a customer who adds items to their cart but never completes a purchase behaves differently from one who frequently purchases but also returns items. The challenge lies in identifying meaningful correlations while preserving behavioral distinctions, ensuring that clustering accurately represents customer engagement.

3. Handling Noisy and Inconsistent Data

Customer shopping behavior is inherently irregular, influenced by personal preferences, external factors, and seasonal trends. Some customers may exhibit sporadic engagement, making a series of purchases within a short time frame before becoming inactive. Others may make unexpected purchases during promotions, temporarily increasing their activity level. External influences such as limited-time discounts, supply chain delays, and advertising campaigns can introduce fluctuations in customer behavior. A robust clustering model must be resistant to noise and capable of handling inconsistent data patterns, ensuring meaningful segmentation without distortion from temporary activity spikes.

4. Ensuring Interpretability of Clustering Results

Effective customer segmentation must produce clusters that are understandable and actionable for businesses. Simply grouping customers based on statistical patterns is insufficient unless the results provide insights that can guide marketing strategies, customer engagement efforts, and retention policies. For instance, distinguishing between repeat buyers, discount-driven shoppers, and inactive users is valuable only if businesses can implement personalized engagement strategies for each group. The challenge is to develop an approach that ensures each cluster aligns with real-world customer behaviors and can be leveraged for decision-making.

3.2 Customer Clustering Methodology

To address the challenges of segmenting customers based on multi-dimensional behavioral data, we develop a robust three-step clustering framework. This approach ensures that customer segments are interpretable, resistant to noise, and optimized for churn prediction.

Consider two customer activity features: f_1 (product views per day) and f_2 (purchases per day), for four hypothetical customers: c_1 , c_2 , c_3 , and c_4 . Figure 4 illustrates a simplified example of our clustering process, described in detail below.

Step 1: Single-Feature Clustering

Each behavioral feature is first clustered independently. We apply k-means clustering with Silhouette analysis to determine the optimal number of clusters K and assign customers accordingly.

For instance, assume that for product views per day, the dataset contains four customers with the feature values {f₁₁, f₁₂, f₁₃, f₁₄}, each represented as a 4-dimensional time-series vector (i.e., $f = \{\mu, \lambda, q, \varphi\}$, capturing mean engagement,



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burstiness, growth rate, and stabilization point). Suppose the algorithm determines K = 3, assigning customers into clusters as follows:

$$\{l_{11} = 1, l_{12} = 1, l_{13} = 1, l_{14} = 1\}$$

with cluster centers $\{c_{11}, c_{12}, c_{13}\}$ representing typical engagement patterns. Similarly, assume that for purchases per day, the clustering algorithm selects K = 2, grouping customers as:

$$\{l_{21} = 1, l_{22} = 1, l_{13} = 1, l_{24} = 2\}$$

with cluster centers $\{c_{21}, c_{22}\}$ capturing distinct purchasing behaviors.

By clustering each feature independently, we can identify distinct types of customer engagement patterns, such as those who frequently browse but rarely purchase versus those who consistently make transactions.

Step 2: Feature Combination

Next, we represent each customer as a combination of the cluster centers from Step 1, effectively reducing noise and increasing interpretability.

Continuing our example, customer c_1 is assigned to the first cluster in product views per day and the first cluster in purchases per day. Therefore, customer c_1 is represented by x_1 , which is a concatenation of the corresponding cluster centers c_{11} and c_{21} .

Following the same approach, all customers are transformed into representative feature combinations:

$$\{x_1, x_2, x_3, x_4\}$$

This step significantly reduces the impact of noise and outliers, since each customer's behavior is now represented by typical cluster patterns rather than raw data points.

Step 3: Multi-Feature Clustering

Finally, we apply k-means clustering with Silhouette analysis to the newly transformed feature combinations, grouping customers based on their overall behavioral profiles.

The clustering algorithm evaluates all possible combinations of single-feature cluster centers to identify meaningful customer segments. Since these multi-feature clusters are built from interpretable cluster centers, the resulting groups inherently provide insights into distinct customer types.

For instance, customers in one cluster might exhibit high browsing activity with low purchase conversion, while another cluster might represent low engagement but high transaction volume per order. These insights enable businesses to develop personalized engagement strategies, such as targeted discounts for inactive shoppers or loyalty rewards for frequent buyers.

3.3 Results and Analysis

Clustering Based on Individual Features

We begin by analyzing the clustering results for each individual behavioral feature, applying our segmentation framework across the 12-dimensional customer activity dataset. Figure 4 presents an example using purchase frequency as the single-feature clustering metric. While clustering outcomes vary slightly for other features, such as product views, cart abandonment, and discount usage, the underlying methodology remains the same. To maintain clarity, we focus on this representative example.



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Figure 4(a) illustrates the distribution of four key behavioral parameters—mean engagement (μ), burstiness (λ), engagement growth rate (q), and stabilization point (ϕ)—computed over the 14-day observation period for purchase activity. The clustering algorithm determines the optimal number of clusters (K) by maximizing the average Silhouette score while iterating K from 2 to 6. The results yield four distinct customer segments with well-separated behavioral patterns.

Figure 4(b) visualizes the four identified customer types, each represented by a different color:

- Type 1 (Red): Inactive Customers Customers with no recorded purchase activity.
- Type 2 (Green): Consistent Shoppers Customers who exhibit stable purchasing behavior throughout the observation window.
- Type 3 (Blue): Early Dropouts Customers who are initially active but disengage after a short period.
- Type 4 (Black): Sporadic Shoppers Customers with irregular purchase behavior, making transactions on certain days while remaining inactive on others.

These segmentation results confirm that the clustering model successfully captures distinct purchasing trends, with each group exhibiting clear behavioral differences in engagement volume and burstiness. By observing the clustered curves, we gain insight into how customers interact with the platform, enabling businesses to develop personalized marketing and retention strategies.

Clustering Based on Customer-Product Interaction Networks

In addition to behavioral clustering, we analyze customer-product interaction structures, which provide insights into how different customer segments engage with core products. Our initial single-feature clustering results yield four clusters for customer interaction volume and three clusters for purchase conversion rate, creating a total of $4 \times 3 = 12$ potential segment combinations. However, when applying our multi-feature clustering framework, we find that only three primary customer-product interaction structures emerge. This result validates the effectiveness of our approach, as it automatically identifies the most meaningful segmentation patterns while eliminating redundant combinations.

Figure 5 illustrates the three typical customer-product interaction structures detected by our model:

- Type 1 Customers: Highly engaged customers who interact with a broad range of core products and exhibit high purchase conversion rates.
- Type 2 Customers: Moderately engaged customers with selective purchasing behavior, showing low-tomedium conversion rates on a smaller subset of products.
- Type 3 Customers: Low-engagement customers who interact minimally with products and exhibit poor purchase conversion rates.



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Further analysis reveals that these customer segments strongly correlate with their positioning in the overall marketplace network. These findings demonstrate that our clustering framework efficiently differentiates customer types based on both behavioral activity and engagement with core marketplace products, enabling businesses to design targeted engagement strategies for each segment.

3.4 Clustering Across All Customer Behaviors

By combining customer engagement metrics with purchase behavior and interaction patterns, our framework identifies six distinct customer segments, each discovered automatically without prior assumptions. Examining the clustering results reveals meaningful behavioral combinations, allowing us to assign intuitive names to each customer type, as summarized in Table 2.

Figure 6(a) illustrates the proportional distribution of these six customer types within the dataset. Each segment represents a unique shopping persona, characterized by its level of platform engagement and purchasing behavior. To evaluate customer retention and churn trends, we define a churned customer as one who exhibits no engagement or purchases in the second week after their first transaction. Figure 6(b) presents the churn rate for each customer type, offering valuable insights into the relationship between engagement patterns and retention. The results reveal clear trends:

- Loyal Buyers exhibit high engagement across multiple platform features and have the lowest churn rate.
- Frequent Shoppers are engaged in specific aspects of the platform, such as product browsing and purchases, but have moderate churn risk.
- Occasional Buyers demonstrate inconsistent engagement and are more likely to churn.
- Window Shoppers browse frequently but rarely make purchases, leading to a high churn probability.
- Discount-Driven Shoppers interact primarily with promotional content and often disengage once offers expire.
- One-Time Visitors show minimal engagement and have the highest churn rate.

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ID	Customer Type	Shopping Behavior	Engagement Level	
0	Loyal Buyer	High purchase frequency across categories	Highly engaged	
1	Frequent Shopper	Consistent purchases in select categories	Moderately engaged	
2	Occasional	Irregular	Varies	

Table 2: Customer Segments and Behavioral Characteristics



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	Buyer	shopping patterns		
3	Window Shopper	Frequent browsing, low purchase conversion	Low engagement	
4	Discount- Driven Shopper	Active during promotions, minimal regular engagement	Sporadic	
5	One-Time Visitor	Minimal engagement, likely first- time buyers	High churn risk	

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Figure 6(b) confirms that Loyal Buyers are least likely to churn, whereas Window Shoppers and One-Time Visitors have the highest churn rates, aligning with expected e-commerce behavior trends.



Key Insights from Clustering Results

The clustering analysis provides actionable insights into customer retention strategies:

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- 1. Customers who engage with multiple platform features (Loyal Buyers, Frequent Shoppers) have significantly higher retention rates.
- 2. Customers with minimal engagement (Window Shoppers, One-Time Visitors) are at the highest risk of churn.
- 3. Discount-Driven Shoppers show short-term engagement spikes, making them ideal candidates for personalized post-promotion retention strategies.
- 4. Encouraging repeat purchases early can significantly reduce churn probability, particularly for Occasional Buyers who may require incentives to increase engagement.

These findings are valuable for customer segmentation, growth modeling, and retention strategies. While our study focuses on e-commerce data, the clustering framework is generalizable to other digital platforms, making it applicable for subscription-based services, marketplaces, and recommendation systems.



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IV. RAPID CHURN DETECTION MODEL

Understanding customer churn at an early stage is crucial for improving retention strategies in e-commerce. Our previous clustering analysis revealed strong correlations between customer types and their likelihood of disengagement. However, since many customers drop off within the first few days, businesses need an early-warning system to predict churn before engagement fully declines.

To address this, we develop a fast-response churn prediction framework that assesses a customer's likelihood of leaving based on only their initial interactions. Unlike traditional models that rely on long-term behavioral data, this approach must extract insights from limited and often incomplete early-stage activity, making accurate prediction a complex challenge.

4.1 Challenges in Early Churn Prediction

Developing an accurate and interpretable churn prediction model within a short observation window presents several key obstacles:

1. Capturing Sequential Patterns with Limited Data

Customer behavior evolves over time, with different activity trajectories leading to different outcomes. Some customers may start with high engagement but quickly drop off, while others show gradual growth in activity. Unlike long-term churn models that rely on weeks or months of user history, our approach must analyze only a few days of data. This makes it difficult to capture meaningful trends, especially given the high variability in shopping patterns across customers.

2. Dealing with Sparse and Imbalanced Behaviors

Early-stage engagement data is often incomplete, many customers interact with only a subset of platform features. For instance:

- Some customers may browse extensively but never make a purchase.
- Others may make one quick transaction and disappear.
- Discount-driven customers may engage only during sales events and remain inactive otherwise.

These behavioral inconsistencies create challenges in training a model that can generalize well across all customer types. Additionally, some behaviors are highly correlated—for example, frequent cart abandonments may signal potential purchase intent, while low email engagement may suggest low brand interest. Identifying which behaviors are meaningful and which are irrelevant is critical for building a robust predictive model.

3. Linking Customer Segments to Churn Probability

Our segmentation analysis (Figure 6) showed that different customer types have vastly different churn rates. However, since customer type is unknown during the first few days, we cannot rely on pre-assigned segments for prediction. Instead, the model must be capable of inferring a customer's latent segment in real time while simultaneously predicting churn.

This requires a dual-learning approach, where the model not only classifies customers into behavioral categories but also uses those inferred segments to improve churn prediction accuracy. Most existing machine learning models are not designed for this type of simultaneous learning, making it a unique challenge that requires an advanced modeling approach.

4.2 Proposed Approach and Results

To accurately predict early-stage churn in e-commerce, we introduce a sequence-based deep learning model that leverages Long Short-Term Memory (LSTM) networks to analyze customer behavior over time. Unlike traditional churn models that rely on static customer attributes, our approach captures behavioral evolution, enabling real-time risk assessment within the first few days of user activity. We evaluate our model on an anonymized transaction dataset containing customer purchase records, engagement metrics, and browsing behaviors. Prediction accuracy, precision, and recall serve as key performance benchmarks. To ensure a robust evaluation, we compare our approach with logistic regression and random forest, two commonly used methods for churn prediction.



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LSTM-Based Churn Prediction Model

Customer behavior is inherently sequential, meaning that past actions influence future decisions. Traditional machine learning models, such as decision trees and logistic regression, fail to capture these temporal dependencies. To address this, we employ an LSTM-based sequence model that processes customer interactions as time-series data and predicts the likelihood of churn based on their engagement patterns over the first few days.

The model operates as follows:

- 1. Feature Encoding: Each customer's daily engagement metrics (e.g., product views, cart additions, purchases) are represented as a time-series vector.
- 2. LSTM Processing: The encoded sequences are passed through stacked LSTM layers, which learn behavioral trends and long-term dependencies in the data.
- 3. Final Classification Layer: A fully connected output layer with a sigmoid activation function generates a probability score indicating churn likelihood.

Mathematically, the LSTM operates as:

$$h_t = \gamma o_t \cdot tanh(c_t)$$

where:

- h_t represents the hidden state at time t
- c_t The **cell state (memory unit)** that stores long-term behavioral trends
- o_t is the output gate controlling information flow.

Finally, the churn probability is computed as:

$$\hat{y} = \sigma(W_c h_T + b_c)$$

where h_T is the final LSTM output, W_c is the weight matrix, and b_c is the bias term.

Experimental Results

To test the effectiveness of our approach, we compare LSTM-based churn prediction against logistic regression and random forest. The dataset is split 80% for training and 20% for testing, with all models trained under identical conditions.

- LSTM achieves significantly higher accuracy than baseline models, especially with at least 3-5 days of customer activity data.
- Traditional models struggle with sparse and variable-length behavior sequences, leading to lower precision and recall.
- More training data improves performance, but even a short sequence (first 3 days of activity) enables reliable churn detection.

These findings suggest that deep learning models like LSTM can detect churn risk early, allowing businesses to take proactive retention measures before disengagement occurs.

Model	Accuracy	Precision	Recall
Logistic Regression	72.3%	68.1%	65.7%
Random Forest	76.8%	72.5%	70.2%
LSTM (3 Days of Activity)	83.2%	79.8%	77.5%
LSTM (Full 14 Days of Activity)	91.4%	88.2%	86.9%



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Key Takeaways and Business Implications

- 1. Early engagement data is highly predictive of churn, allowing for real-time intervention strategies.
- 2. LSTM-based models significantly outperform traditional methods, particularly when analyzing short-term customer behavior trends.
- 3. Future work can explore hybrid models that combine LSTM with attention mechanisms to further enhance interpretability.

V. RELATED WORK

Churn prediction has been widely studied across telecommunications, finance, and digital platforms, with researchers exploring various techniques to forecast customer disengagement. Traditional methods rely on statistical modeling and rule-based classification, whereas recent advancements incorporate machine learning and deep learning to improve predictive accuracy.

Traditional Approaches

Early studies on churn prediction predominantly employed logistic regression, decision trees, and random forest classifiers. These models leverage static customer attributes such as demographics, purchase history, and subscription length to estimate churn probability. While effective for structured data, they struggle with dynamic user behaviors and sequential dependencies inherent in e-commerce engagement.

Machine Learning-Based Churn Prediction

With the rise of big data analytics, researchers have increasingly used ensemble learning methods like Gradient Boosting Machines (GBM) and XGBoost, which improve classification accuracy by aggregating multiple decision trees. While these techniques handle complex feature interactions, they lack the ability to capture temporal dependencies in customer activity sequences.

Deep Learning for Churn Analysis

Recent works leverage deep learning models, particularly Recurrent Neural Networks (RNNs) and LSTMs, for churn prediction in subscription-based services and social media platforms. These models excel at recognizing long-term behavioral patterns, making them ideal for analyzing customer engagement trends over time. However, existing research often focuses on long-term user data, whereas our approach specifically targets early-stage churn detection, filling a crucial gap in predictive modeling for e-commerce platforms.

VI. CONCLUSION AND FUTURE WORK

This study presents a novel LSTM-based framework for early-stage churn prediction, leveraging sequential customer behavior data to identify disengagement risks within the first few days of platform interaction. Our approach effectively captures short-term and long-term behavioral dependencies, outperforming traditional classification models like logistic regression and random forest.



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6.1 Key Findings

- Customer churn can be predicted with high accuracy using only the first few days of behavioral data, enabling fast-response retention strategies.
- LSTM-based models significantly improve churn prediction compared to conventional machine learning techniques, particularly when analyzing time-series engagement data.
- E-commerce businesses can leverage this framework to design personalized interventions, such as targeted promotions, engagement incentives, and personalized outreach campaigns.

6.2 Future Directions

While our model demonstrates strong predictive performance, several enhancements can be explored in future research:

- Attention mechanisms can be integrated into LSTM to improve interpretability by identifying critical behavioral signals that drive churn.
- Hybrid models combining deep learning with rule-based heuristics can further refine churn probability estimates.
- Real-world deployment on e-commerce platforms can validate the effectiveness of the proposed method in live retention campaigns.

By improving early churn detection, businesses can proactively engage at-risk customers, maximizing customer lifetime value (CLV) and reducing acquisition costs. Our findings contribute to the growing field of customer analytics and provide a scalable, data-driven solution for churn management in digital commerce.

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