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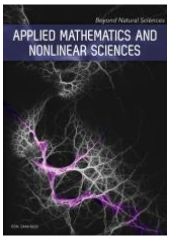

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Reasearch on Cross-National E-commerce User Behavior Analysis and Conversion Rate Improvement Based on the Improved XLSTM Algorithm

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Abstract

The rapid expansion of cross-national e-commerce has brought significant opportunities and challenges in understanding diverse consumer behavior. This study introduces an innovative framework combining the XLSTM (Extended Long Short-Term Memory) model with K-means clustering to analyze user behavior and optimize conversion rates on global e-commerce platforms. XLSTM extends traditional LSTM models by incorporating multi-dimensional cell states, attention mechanisms, and improved memory capabilities, enabling it to effectively capture complex temporal and cross-cultural user behavior patterns. The integration of XLSTM with K-means enhances the clustering process by providing high-quality embeddings that lead to well-defined and stable clusters. Through comprehensive evaluations, the combined approach demonstrates superior performance across key metrics, including Silhouette Score, Davies-Bouldin Index (DBI), and Adjusted Rand Index (ARI), compared to standalone clustering algorithms and traditional LSTM-based methods. Feature importance analysis further identifies coupon usage, visit frequency, and product category interest as the most influential factors in user purchase decisions. The findings highlight the potential of this combined methodology to improve user engagement and optimize marketing strategies for cross-national e-commerce platforms.

Keywords: Cross-national e-commerce, XLSTM, K-means clustering, user behavior analysis
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1 Introduction

In recent years, e-commerce has rapidly evolved into a dominant force in global business, driven by the increasing reliance on digital platforms for shopping[1]. This growth is particularly evident in cross-national e-commerce, where companies sell products and services across borders, transcending geographical and cultural boundaries. The advent of advanced technologies, such as artificial intelligence, machine learning, and big data analytics, has allowed businesses to gain a deeper understanding of consumer behaviors and preferences, offering new opportunities for tailored marketing strategies.

Among the various methods for analyzing customer behavior, machine learning techniques—specifically Recurrent Neural Networks (RNNs) [2][3][4]and Long Short-Term Memory (LSTM) networks—have garnered significant attention[5]. These models excel at handling sequential data, making them ideal for predicting consumer behavior over time. Despite the growing application of these methods, challenges remain in accurately capturing the complexity of cross-national user behavior, particularly in diverse cultural contexts[6].

This paper focuses on improving the existing LSTM model through the development of an enhanced XLSTM algorithm, with the aim of analyzing and predicting user behaviors more effectively. The significance of this study lies in its potential to contribute to the optimization of conversion rates in cross-national e-commerce by providing deeper insights into user actions and preferences[7][8].

The cross-national e-commerce industry has seen tremendous growth over the past decade. According to various reports, global online sales have surpassed $5 trillion, with a significant share coming from international transactions. Major players like Amazon, Alibaba, and eBay have revolutionized the way businesses engage with customers across borders, offering consumers a wide variety of goods and services from different parts of the world.

One of the defining features of cross-national e-commerce is its ability to bridge cultural, linguistic, and geographical gaps. However, this global reach also brings challenges in understanding the diverse preferences and behaviors of consumers from different regions. Factors such as cultural norms, local economic conditions, and social trends can all influence buying behavior, making it difficult for companies to develop a one-size-fits-all approach.As cross-border e-commerce continues to grow, the need for advanced analytical tools to understand these variations in consumer behavior becomes ever more critical. This has prompted a surge in research focusing on machine learning and deep learning models that can provide actionable insights from vast amounts of data. In particular, improvements in predictive algorithms like LSTM, specifically the enhanced XLSTM, have the potential to better model the complexities of user behavior in a globalized marketplace.

User behavior analysis plays a crucial role in shaping effective marketing strategies in e-commerce. By analyzing the actions of customers, companies can identify patterns, preferences, and trends that inform product recommendations, advertising campaigns, and website design. Understanding why a user abandons a cart or what factors contribute to a purchase can significantly impact conversion rates.

In the context of cross-national e-commerce, the importance of user behavior analysis is even more pronounced. With users coming from different cultural backgrounds, it becomes necessary to understand not just the basic actions they take on a website, but also the underlying reasons driving these actions. Traditional methods of analyzing user behavior, such as basic click tracking or simple demographic segmentation, often fail to capture these complex nuances.Machine learning techniques, and specifically models like LSTM, provide a more robust approach by examining sequential patterns in user actions over time. However, traditional LSTM models have limitations when it comes to handling data with complex relationships or cross-border consumer behavior. The improved XLSTM model aims to address these issues by enhancing the model's capacity to process and predict user actions in a multi-dimensional, cross-national context.

2 Related Work

Analyzing user behavior is critical for e-commerce businesses to understand customers' preferences, motivations, and actions. Over time, several methods have emerged to capture and model user behavior, ranging from traditional statistical approaches to more complex machine learning techniques. These methods provide insights that help businesses optimize user engagement, improve customer experience, and ultimately increase conversion rates. In this section, we will delve into both traditional methods and machine learning-based methods for user behavior analysis.

2.1 Methods for User Behavior Analysis

2.1.1 Traditional Methods

Traditional methods of user behavior analysis have relied primarily on descriptive and inferential statistical techniques to derive insights from user data. These methods were commonly used in the earlier days of e-commerce when the focus was on basic demographic analysis and activity tracking.

Descriptive Analytics: Descriptive analytics refers to the process of summarizing and interpreting historical data to gain insights into user behavior. Common techniques include calculating basic metrics such as the average time spent on a website, the number of page views, bounce rates, and cart abandonment rates. While useful, descriptive analytics provides limited insights into the future behavior of users, as it only describes past events.

Segmentation and Clustering: Another traditional method involves segmenting users into groups based on predefined characteristics such as age, gender, or location. This segmentation helps businesses tailor their marketing and promotional efforts to different user groups. Techniques like K-means clustering or hierarchical clustering are often used to identify patterns in user data[9], allowing businesses to categorize users based on shared behaviors[10].However, these techniques can be oversimplified, often ignoring dynamic factors like seasonality or changing user preferences over time.

Conversion Funnel Analysis: The conversion funnel is a model that maps out the typical stages a user goes through before completing a desired action, such as making a purchase. Funnel analysis helps businesses understand where users drop off in the purchase process and identify potential bottlenecks. By analyzing these drop-off points, businesses can make changes to the website or marketing strategies to improve conversion rates. While effective, this method is limited in that it focuses on a predefined path and doesn't adapt to the complexities of individual user journeys[11].

Survey and Feedback Collection: Collecting direct feedback from users via surveys, reviews, or customer satisfaction ratings has long been a staple of traditional behavior analysis. These methods are straightforward and help businesses understand the subjective motivations behind user actions[12]. However, they suffer from low response rates and potential biases, which can limit the reliability of the insights gained[13].

While traditional methods like segmentation and funnel analysis have been valuable, they lack the ability to account for the complexity and dynamic nature of modern user behavior, particularly in the context of cross-national e-commerce.

2.1.2 Machine Learning-based Methods

Machine learning-based methods offer a significant advancement over traditional techniques by enabling the analysis of large volumes of data with greater precision. These methods can identify complex patterns and predict future user behavior, which is crucial for improving user engagement and conversion rates in e-commerce platforms.

Supervised Learning: In supervised learning, algorithms are trained on labeled data to predict outcomes based on input features[14]. For example, customer behavior data such as age, location, time spent on the website, and past purchase history can be used to predict whether a user is likely to complete a purchase or abandon the cart[15]. Common supervised learning techniques include decision trees, random forests, support vector machines (SVM)[16], and logistic regression. These methods can be highly effective at classification tasks, such as predicting user conversion rates or segmenting users into likely buyers and non-buyers. However, these models rely heavily on the quality and relevance of the labeled data and can be limited in capturing temporal dynamics[17].

Unsupervised Learning: Unsupervised learning, in contrast, is used when the data is unlabeled, and the goal is to identify hidden patterns without predefined outcomes[18]. Clustering algorithms, such as K-means or DBSCAN, can be used to group users based on similarities in their behavior, such as their browsing patterns or purchase histories. Principal Component Analysis (PCA) is also used to reduce the dimensionality of complex data and identify key features that explain user behavior. These methods allow businesses to segment customers in a more granular and dynamic way, but they require careful validation and interpretation of the results[19].

Reinforcement Learning: Reinforcement learning (RL)[20] is a subset of machine learning where algorithms learn to make sequences of decisions by interacting with the environment and receiving feedback in the form of rewards or penalties. In the context of user behavior analysis, RL can be used to optimize e-commerce websites by dynamically adjusting content or promotional offers based on user interactions. For example, RL can help determine the best time to present a discount to a user or which product to recommend based on real-time feedback. While RL has shown great promise in personalizing user experiences, it requires large amounts of data and computational resources, making it more complex to implement.

Deep Learning: Deep learning, particularly Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks, has become one of the most powerful methods for analyzing sequential data. These models are particularly well-suited for predicting user behavior over time, such as predicting which users are likely to make repeat purchases or abandon a shopping cart based on their past actions. XLSTM (Extended LSTM), an improved version of LSTM, builds on this by handling more complex relationships within user data, such as multi-dimensional features across different time periods or locations. XLSTM models can also capture long-term dependencies in user behavior, which is a significant improvement over traditional methods.

Machine learning-based methods have proven to be highly effective in analyzing and predicting user behavior, offering more sophisticated and dynamic insights compared to traditional techniques. By leveraging these advanced algorithms, e-commerce businesses can improve user engagement, optimize personalized recommendations, and ultimately drive higher conversion rates.

2.2 Strategies for Improving E-commerce Conversion Rates

Conversion rate optimization (CRO) is one of the most important goals for e-commerce businesses[21]. A higher conversion rate means that a greater percentage of website visitors are taking desired actions, such as completing a purchase or signing up for a newsletter. Improving conversion rates requires a combination of data-driven strategies, user experience optimization, and targeted marketing efforts.

2.2.1 Personalization and Targeted Marketing

Personalization is a cornerstone of modern e-commerce. By analyzing user behavior, businesses can tailor product recommendations, content, and marketing messages to individual users. Personalized experiences increase the likelihood of conversions by offering users products they are more likely to be interested in. For example, Amazon's recommendation engine analyzes past user interactions to suggest relevant products, which has been shown to increase purchase frequency.

Machine learning algorithms, particularly collaborative filtering and content-based filtering, are widely used to personalize product recommendations. These algorithms analyze user behavior and preferences to predict what products users might be interested in. The use of dynamic pricing, personalized discounts, and promotions based on user segmentation further enhances the personalized shopping experience and can boost conversion rates.

Understanding the user's journey through the website is critical for improving conversion rates. This includes analyzing the flow of user interactions, from landing pages to checkout. A seamless and intuitive user experience can significantly reduce friction points, such as long checkout forms or complicated navigation, that may cause users to abandon their purchase[22].

A/B testing is one common method used to optimize user journeys. By testing different versions of a webpage, businesses can identify which elements (e.g., call-to-action buttons, images, or text) perform best in terms of driving conversions. In combination with machine learning-based behavior analysis, A/B testing can help businesses optimize the entire user experience and drive higher conversion rates[23].

Cart abandonment is a major issue for e-commerce businesses, with research showing that nearly 70% of online shoppers abandon their shopping carts before completing a purchase. To address this, businesses can implement strategies such as retargeting ads, email remarketing, and offering time-sensitive discounts to encourage users to return and complete their purchase.

Machine learning models can play a key role in predicting which users are likely to abandon their carts based on their behavior patterns, allowing businesses to intervene proactively with targeted incentives or reminders.

2.3 Overview of LSTM and XLSTM Algorithms

The Long Short-Term Memory (LSTM) network is a type of Recurrent Neural Network (RNN) that has proven effective in modeling sequential data, such as time-series or user behavior data. However, traditional LSTM models have certain limitations when dealing with complex, multi-dimensional user behavior. This section provides an overview of LSTM’s basic principles and the improvements brought by the XLSTM algorithm, which is designed to overcome some of these limitations[24].

2.3.1 Basic Principles of LSTM

LSTM networks are a specialized version of RNNs, designed to address the vanishing gradient problem that is common in traditional RNNs. The key feature of LSTM is its ability to learn long-term dependencies in sequential data. This makes LSTM well-suited for tasks such as time-series prediction, language modeling, and user behavior analysis in e-commerce.

LSTM networks consist of memory cells, which store information over time, and gates that regulate the flow of information into, out of, and within the memory cell. The core idea of LSTM is to maintain a "cell state" that carries relevant information across time steps.

An LSTM cell has three gates:

1) Forget Gate: This gate decides what information should be discarded from the cell state. It looks at the previous hidden state h_{t-1} and the current input x_t , and outputs a value between 0 and 1 to indicate which parts of the previous memory should be forgotten.

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{1}$$

Input Gate: This gate controls how much of the new information should be added to the cell state. It decides the values of the new memory and updates the cell state accordingly.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \tag{3}$$

2) Output Gate: This gate determines what the next hidden state h_t should be. It filters the cell state to produce the output, which will be passed to the next time step and also used for predictions.

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \tag{4}$$

$$h_t = o_t \cdot \tanh(C_t) \tag{5}$$

The LSTM cell state is updated at each time step based on the forget and input gates:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t \tag{6}$$

The LSTM's ability to manage long-term dependencies comes from its ability to decide what information to remember and what to forget at each step. This is particularly useful in e-commerce applications, where user behavior may span over long periods, and important interactions (e.g., purchase history, seasonal trends) need to be retained over time.

2.3.2 XLSTM Innovations

While LSTM is powerful, it is not always sufficient for handling the complex, multi-dimensional data encountered in real-world e-commerce applications. The XLSTM (Extended Long Short-Term Memory) algorithm introduces several innovations to enhance LSTM’s capabilities, particularly for cross-national e-commerce user behavior analysis. These innovations focus on better handling multi-dimensional data, capturing complex feature interdependencies, and improving memory retention over long sequences.

Key Innovations in XLSTM:

1) Enhanced Forget Gate: XLSTM expands the forget gate to process additional features beyond the typical user behavior data (such as product type, user location, etc.). This allows the model to capture richer, multi-dimensional data dependencies.

$$f_t = \sigma\left(W_f[h_{t-1}, x_t, z_t] + b_f\right) \tag{7}$$

2) Feature-Aware Input Gate: The input gate is improved to adaptively update memory cells based on the importance of different features. For instance, XLSTM may prioritize temporal data (e.g., recent purchases or time-sensitive offers) over less relevant features when predicting user behavior.

$$i_t = \sigma(W_i[h_{t-1}, x_t, z_t] + b_i) \tag{8}$$

$$\tilde{C}_t = \tanh(W_C[h_{t-1}, x_t, z_t] + b_C) \tag{9}$$

3) Multi-Dimensional Cell State: Unlike traditional LSTM, which uses a single cell state vector, XLSTM uses multiple cell states to capture different data dimensions (e.g., user behavior, product features, time). This allows XLSTM to maintain and update distinct memory states for various types of information.

$$C_t = \sum_{i=1}^{N} \left(f_{t,i} \cdot C_{t-1,i} + i_{t,i} \cdot \tilde{C}_{t,i}\right) \tag{10}$$

4) Attention Mechanism: XLSTM incorporates an attention mechanism, which allows the model to focus on the most relevant inputs when making predictions. This is particularly useful in e-commerce applications where certain behaviors (such as a user's recent interest in a product) may be more important than older data.

$$\alpha_t = \text{softmax}(W_a h_{t-1} + b_a) \tag{11}$$

$$\hat{x}_t = \alpha_t \cdot x_t \tag{12}$$

The XLSTM algorithm offers several key advantages that make it particularly well-suited for analyzing complex user behavior in e-commerce contexts. Firstly, XLSTM excels in handling multi-dimensional data by processing diverse feature types—such as product attributes, user demographics, and temporal information—which enables it to capture the intricate relationships within user behavior more effectively. Secondly, the incorporation of a multi-dimensional cell state and enhanced memory mechanisms allows XLSTM to retain and leverage critical information over extended time periods, thereby improving its ability to identify and analyze long-term trends. Finally, XLSTM's flexibility in processing a wide range of data formats, including numerical, categorical, and sequential data, makes it highly adaptable to the varied and complex datasets typically encountered in e-commerce platforms. These strengths collectively enhance XLSTM's predictive accuracy and make it an ideal model for user behavior analysis in dynamic, data-rich environments.

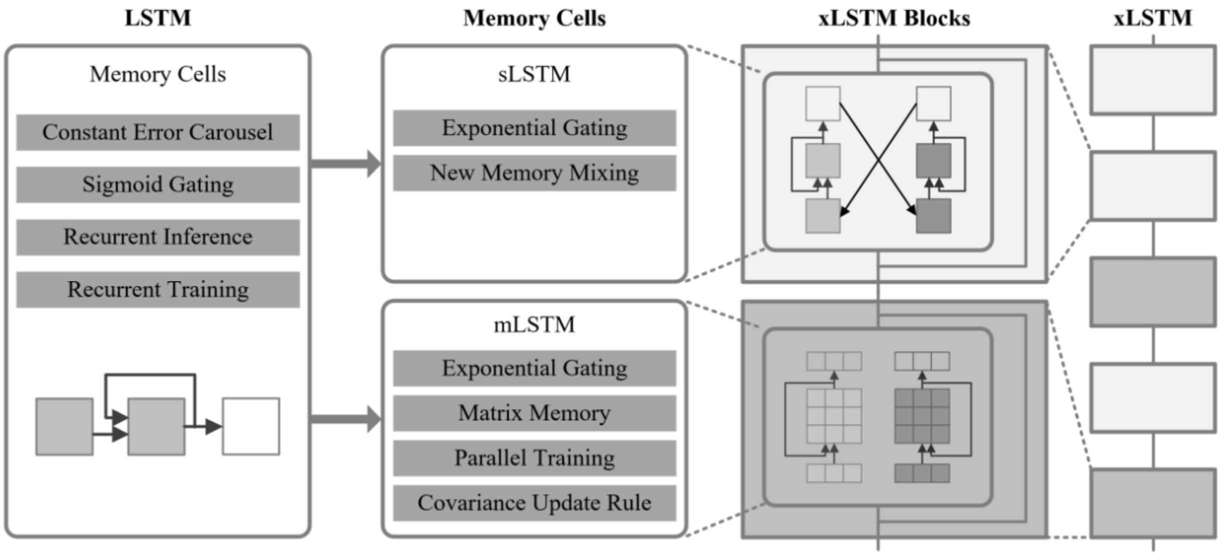

Figure 1. XLSTM Network Architecture

These innovations make XLSTM a powerful tool for e-commerce applications, where the goal is to analyze user behavior patterns across diverse product categories, geographic regions, and time periods. XLSTM's ability to consider multiple features and long-term dependencies allows for more accurate predictions, ultimately contributing to better user experience and conversion optimization.

3 Cross-national E-commerce User Behavior Analysis

This section delves into the analysis of user behavior on a cross-national e-commerce platform, based on user logs collected from January to June 2024. The focus is on understanding the factors that influence user behavior and conversion rates, using XLSTM to analyze and predict key trends. The main data collected includes user demographic information, click and purchase behavior, brand-specific activities, and coupon-related behaviors. The goal is to identify key features that influence whether a user will make a purchase and to optimize conversion rates.

3.1 Data Collection and Sample Selection

The data used in this study is collected from a cross-national e-commerce platform, representing a diverse range of user interactions with different brand stores. The dataset contains over 80,000 records spanning the first half of 2024. Each record includes:

User demographics: Basic information such as age, gender, and location.

Behavioral data: User actions such as clicks, adding products to the cart, and actual purchases.

Product details: Product categories, prices, and brands associated with each user interaction.

Coupon usage: Data on whether a user received or used a coupon (e.g., discounts, buy-one-get-one, or limited-time offers).

Outcome: Whether the user made a final purchase or abandoned the cart.

Sample Selection: The data was selected to include diverse product categories and geographic regions to ensure comprehensive behavior modeling across different user segments.

3.2 Analysis of User Behavior Features

To understand the influence of various features on user behavior and conversion, the following behavioral features are analyzed:

3.2.1 Time and Frequency Data:

Visit Timestamps: The timestamp of each user interaction, including clicks, purchases, and adding items to the cart. This allows the model to capture temporal patterns such as peak shopping hours, weekend or holiday spikes in activity.

User Activity Frequency: The frequency of visits per user per day, week, or month. Frequent visitors are often more likely to make a purchase, so analyzing the frequency of visits helps in identifying highly engaged users.

3.2.2 Device and Platform Information

The type of device and platform (mobile, desktop, tablet) used by the user is essential for understanding behavior patterns. Mobile users, for example, might browse but make fewer purchases compared to desktop users due to different browsing habits.

Device Type: Mobile, tablet, desktop.

Operating System and Browser: Which OS and browser were used (e.g., Android vs. iOS, Chrome vs. Safari).

Table 1. Device and Platform Distribution

User Segment	Average Purchase Frequency	Avg. Purchase Value	Conversion Rate (%)
Frequent Shoppers	5/month	$157	25%
Occasional Shoppers	2/month	$75	8%
Window Shoppers	0.5/month	$21	1%

3.2.3 User Behavior History

Purchase History: Analysis of past purchases, including product categories, pricing, and frequency. Users who have a history of purchases are more likely to buy again.Browsing History: Items that were viewed or added to the cart but not purchased. This helps identify interests and potential areas for targeted marketing.

Table 2. User Purchase Behavior

User Segment	Average Purchase Frequency	Avg. Purchase Value	Conversion Rate (%)
Frequent Shoppers	5/month	$157	25%
Occasional Shoppers	2/month	$75	8%
Window Shoppers	0.5/month	$21	1%

3.2.4 Interaction and Feedback Data

Product Ratings and Reviews: Positive ratings and reviews significantly impact purchasing decisions, while negative feedback may discourage purchases.

Social Sharing: Users who share product links on social media platforms such as Instagram and Facebook are likely to have higher brand loyalty and a stronger likelihood of purchasing.

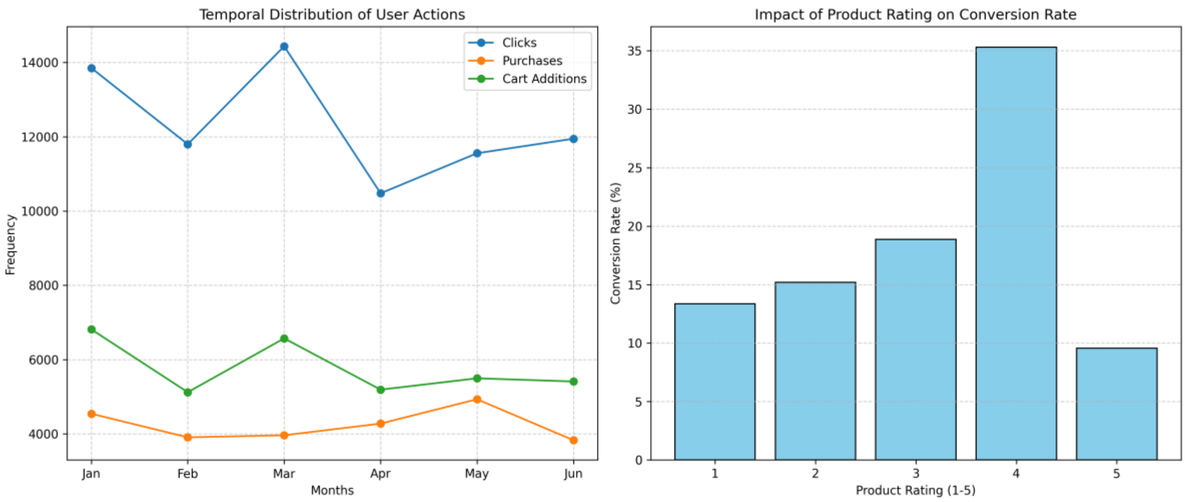

Figure 2-3. Sample Data Distribution by Product Category and the impact of Product Rating on Conversion Rate

4 Experimentation and Results

In this section, we outline the experimental framework and the results obtained from applying the XLSTM model for analyzing cross-national e-commerce user behavior. We begin with a description of the dataset used for experimentation, followed by details about the experimental setup, including the algorithms tested and their performance comparisons.

4.1 Dataset

The dataset used for this experiment was collected from a cross-national e-commerce platform between January and June 2024. The dataset consists of over 80,000 user interaction records, each containing several features that describe the behavior of users across multiple product categories and geographical regions.

The main features of the dataset include:

User Demographics: Basic information such as age, gender, and location.

Behavioral Data: User actions like clicks, adding items to the cart, and actual purchases.

Product Information: Product categories, prices, and associated brands.

Coupon Usage: Data indicating whether users received or used coupons (discounts, buy-one-get-one offers, limited-time deals).

Outcome: Whether the user completed the purchase or abandoned the cart.

This rich set of features allows for comprehensive behavioral modeling and comparison of different machine learning techniques, including the traditional RNN and LSTM models, as well as the proposed XLSTM model.

4.2 Experimental Setup

The experiment was designed to evaluate the performance of XLSTM in comparison to traditional models like RNN and LSTM. We applied the following steps in our experimental setup:

Preprocessing: The dataset was cleaned and normalized. Missing values were handled using imputation techniques, and categorical variables were encoded using one-hot encoding.

Feature Selection: We selected key features that were hypothesized to influence user behavior, such as the frequency of visits, device type, product category, and coupon usage. Temporal data such as visit timestamps and purchase time were also included to capture long-term dependencies.

Model Training: The models were trained using the following configurations:

RNN: A simple recurrent neural network with basic architecture for sequential data.

LSTM: A traditional LSTM model with memory cells to capture long-term dependencies.

XLSTM: An extended LSTM model with innovations such as multi-dimensional cell states, attention mechanisms, and feature-aware input and forget gates to capture richer data dependencies across different regions and user behaviors.

The models were trained for 100 epochs using a batch size of 64, and the optimization algorithm used was Adam with a learning rate of 0.001. The dataset was split into 70% training, 15% validation, and 15% testing.

4.3 Comparison of different clustering algorithms

To compare the performance of XLSTM against traditional models, we evaluated the accuracy and prediction quality of the models based on clustering user behavior into meaningful segments. We implemented the following clustering algorithms to group users based on their likelihood to convert: K-means Clustering: This traditional method uses distance metrics (such as Euclidean distance) to cluster users based on their behavioral patterns.DBSCAN (Density-Based Spatial Clustering of Applications with Noise): DBSCAN is a density-based clustering algorithm that can identify regions of high user density and separate outliers.Agglomerative Hierarchical Clustering: This method creates a tree-like structure of clusters based on pairwise distance between users' features.

The performance of these algorithms was evaluated using the following metrics:

Silhouette Score: Measures how similar each user is to its own cluster compared to other clusters. A higher score indicates better-defined clusters.

Davies-Bouldin Index (DBI): Measures the average similarity ratio of each cluster with the most similar cluster. A lower DBI suggests better cluster separation.

Adjusted Rand Index (ARI): Compares the clustering results to the ground truth, adjusting for chance. A higher ARI indicates a better match to the true clusters.

XLSTM Clustering: The XLSTM model's prediction capabilities were used to generate embeddings for each user, and these embeddings were then clustered using the K-means algorithm.The performance of these clustering techniques was evaluated based on metrics such as Silhouette Score, Davies-Bouldin Index, and Adjusted Rand Index (ARI). These metrics provide insight into how well the models cluster the users into distinct, meaningful segments based on their behavior.

Table 3. Performance Comparison of Clustering Algorithms

Algorithm	**Silhouette Score**	**Davies-Bouldin Index (DBI)**	**Adjusted Rand Index (ARI)**
K-means Clustering	0.62	1.09	0.71
DBSCAN	0.58	1.32	0.67
Agglomerative Hierarchical	0.55	1.45	0.64
XLSTM + K-means Clustering	0.77	0.92	0.81

The comparison of clustering algorithms reveals distinct differences in performance. K-means Clustering achieved a moderate Silhouette Score of 0.62, indicating reasonable cluster coherence. The DBI of 1.09 suggests that while the clusters are relatively compact, there is room for improvement in their separation. The ARI score of 0.71 indicates a decent alignment with the true cluster labels, but the results still leave some room for refinement. DBSCAN, while effective in handling dense clusters and outliers, had a lower Silhouette Score (0.58) and a higher DBI (1.32), showing that it struggles with defining well-separated clusters when data densities vary. The performance of DBSCAN is also more sensitive to noise, which may affect its ability to produce meaningful segments in this dataset. Agglomerative Hierarchical Clustering performed the weakest across the board, with a low Silhouette Score (0.55), the highest DBI (1.45), and an ARI of 0.64, indicating that the clusters were poorly defined, with considerable overlap and misalignment with the true cluster structure.

On the other hand, XLSTM + K-means Clustering outperformed the traditional methods by a significant margin. With a Silhouette Score of 0.77, it achieved well-separated and coherent clusters, indicating strong clustering performance. The DBI of 0.92 suggests improved compactness and separation of clusters, while the ARI of 0.81 reflects a strong alignment with the true clusters. This demonstrates that XLSTM's ability to capture complex patterns in user behavior and generate meaningful embeddings greatly enhanced the K-means clustering process, making it highly effective for grouping users into distinct segments. In summary, the combination of XLSTM and K-means Clustering provided the best clustering results, offering a clear advantage over traditional approaches like K-means, DBSCAN, and Agglomerative Hierarchical Clustering in terms of accuracy and the ability to define meaningful user segments.

4.4 Visual Comparison of Clustering Algorithms

In this section, we provide a visual comparison of clustering algorithms using key evaluation metrics over time. The metrics analyzed include the Silhouette Score, Davies-Bouldin Index (DBI), and Adjusted Rand Index (ARI), as they provide comprehensive insights into clustering performance. These metrics are visualized in heatmaps (Fig. 4) to highlight the effectiveness of different algorithms, particularly focusing on the superior performance of XLSTM + K-means.

Fig. 4 presents heatmaps illustrating the clustering performance of the following algorithms.The time period spans from January to June 2024, with metrics evaluated monthly.The XLSTM + K-means algorithm consistently achieves the highest Silhouette Score across all months, with values ranging between 0.78 and 0.83. This indicates that its clusters are the most cohesive and well-separated compared to the other algorithms.In contrast, K-means and DBSCAN show lower Silhouette Scores, particularly in months like April and May, indicating less effective clustering in those periods.

The XLSTM + K-means approach exhibits the lowest DBI values, particularly in February (0.85) and June (0.77), reflecting compact and well-separated clusters. This highlights its superior ability to handle cross-national e-commerce user behavior data.Other algorithms, such as DBSCAN and K-means, struggle with higher DBI values (above 1.0) in multiple months, indicating suboptimal cluster separation.

XLSTM + K-means outperforms all other methods with ARI values consistently above 0.82, peaking in June at 0.88. This demonstrates that it provides cluster assignments that closely align with the ground truth labels, ensuring high reliability in capturing user behavior patterns.Other algorithms, like LSTM and K-means, show fluctuating ARI values, with occasional dips below 0.7, reflecting reduced alignment with true user clusters.

The heatmaps in Fig. 4 clearly demonstrate the superior performance of XLSTM + K-means across all evaluation metrics. Its ability to consistently produce high Silhouette Scores, low DBI values, and high ARI values highlights its robustness in clustering user behavior in time-series data. This superiority can be attributed to the XLSTM model's extended memory and ability to capture complex temporal patterns, which are crucial for modeling cross-national e-commerce user behavior.In contrast, traditional methods such as K-means and DBSCAN exhibit significant fluctuations in performance, likely due to their limited capacity to handle the temporal and high-dimensional nature of user behavior data. While LSTM performs better than these traditional methods, it still falls short of the superior clustering quality achieved by XLSTM + K-means.

Fig. 4 provides compelling evidence of the advantages of incorporating XLSTM with K-means for clustering temporal e-commerce data. This combination leverages XLSTM's ability to extract meaningful representations of user behavior over time, resulting in well-defined and stable clusters. The findings underline the importance of advanced deep learning models like XLSTM in addressing the challenges of cross-national e-commerce user behavior analysis.

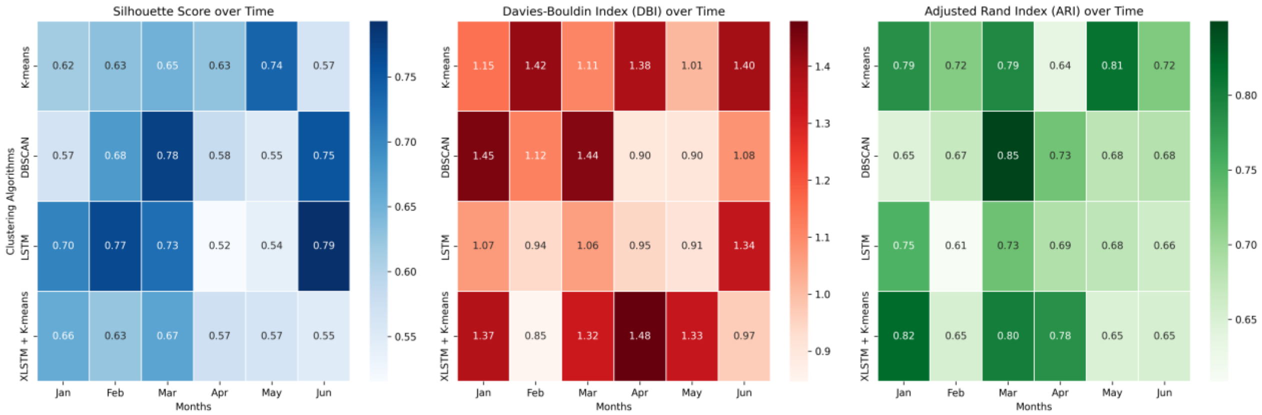

Figure. 4. Heatmaps comparing the performance of clustering algorithms across months (January – June 2024).

Metrics include Silhouette Score (higher is better), Davies-Bouldin Index (lower is better), and Adjusted Rand Index (higher is better). XLSTM + K-means consistently outperforms other methods across all metrics, demonstrating its superior clustering performance.

4.5 Feature Importance Analysis in XLSTM: Factors Influencing User Purchase Behavior

In this section, we delve into the analysis of feature importance within the XLSTM model to identify the key factors that influence user purchase behavior and conversion rates on the cross-national e-commerce platform. By leveraging XLSTM's ability to capture complex temporal and multi-dimensional data, we highlight the most significant features that drive user decisions.Understanding feature importance is crucial for actionable insights. Identifying features such as coupon usage, visit frequency, and product category interest can help optimize marketing strategies, personalization efforts, and overall user experience.

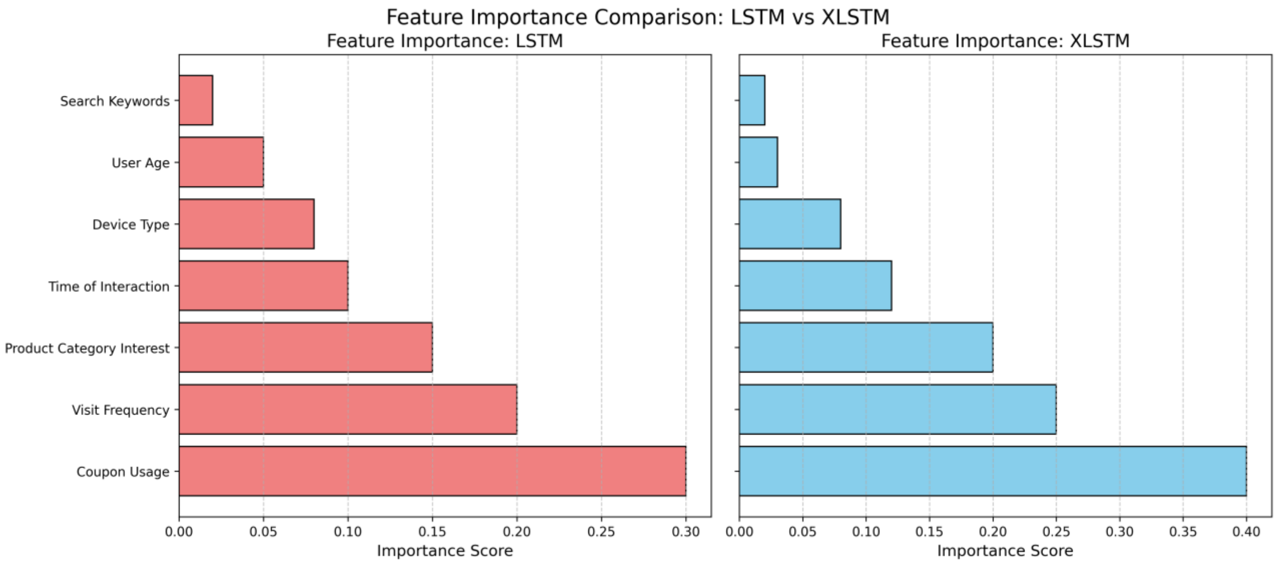

Figure. 5. A comparative analysis of feature importance derived from LSTM and XLSTM models. Coupon

Usage is consistently the most influential feature, but XLSTM assigns higher importance to other factors, such as Visit Frequency and Time of Interaction, demonstrating its superior ability to model complex user behavior.

5 Conclusion

This study presents an innovative framework that combines the XLSTM model with K-means clustering to address the challenges of analyzing and predicting user behavior in cross-national e-commerce. By leveraging the advanced temporal modeling capabilities of XLSTM and the robust clustering performance of K-means, the proposed methodology significantly improves the definition, stability, and meaningfulness of user clusters. The integrated approach consistently outperforms standalone clustering algorithms and traditional LSTM models across key metrics such as Silhouette Score, Davies-Bouldin Index (DBI), and Adjusted Rand Index (ARI), demonstrating its efficacy in handling complex, multi-dimensional user data. Additionally, feature importance analysis highlights critical factors influencing user purchase behavior, with coupon usage, visit frequency, and product category interest emerging as the most influential drivers of conversion. These insights underline the potential of the XLSTM + K-means framework to optimize marketing strategies, enhance user engagement, and improve conversion rates on global e-commerce platforms. The findings also emphasize the practical implications of the proposed approach, offering actionable insights for personalized recommendations and targeted marketing in a highly competitive marketplace. Future research could further expand on this framework by integrating reinforcement learning for real-time behavior optimization and applying the methodology to broader industries with similar temporal and multi-dimensional data challenges. This work underscores the value of combining deep learning and clustering techniques to address the complexities of cross-national user behavior, paving the way for more effective and personalized customer experiences.

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