

Artificial Intelligence-Based Consumer Behavior Analysis for Cross-Border E-Commerce Optimization

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Abstract – Artificial intelligence (AI) has become an important technology for improving customer engagement, personalized marketing, and operational efficiency in cross-border e-commerce platforms. With the rapid growth of digital commerce and online consumer activities, understanding customer purchasing behavior through AI-driven analytics has become increasingly valuable for modern business optimization. This research presents an AI-based consumer behavior analysis framework for cross-border e-commerce optimization using multiple real-world datasets, including customer demographic information, shopping behavior data, social media advertising interactions, recommendation system data, and online purchase intention records. The study applies machine learning models, including Random Forest and XGBoost, to predict customer purchase decisions and analyze factors influencing online consumer behavior. Data preprocessing, feature engineering, exploratory data analysis, and classification techniques were implemented using Python-based analytics tools. Experimental results demonstrate that AI-driven models can effectively predict purchasing behavior and identify important factors affecting customer engagement and online purchase intention. The findings indicate that customer browsing behavior, social media advertising interaction, recommendation systems, and demographic characteristics significantly influence cross-border e-commerce purchasing decisions. This research contributes to the development of intelligent digital commerce systems by integrating AI analytics, consumer behavior analysis, and recommendation-based optimization strategies. The proposed framework provides practical insights for improving customer targeting, personalized marketing, and operational performance in international e-commerce environments.

Keywords – Artificial Intelligence, Consumer Behavior, Cross-Border E-Commerce, Machine Learning, Purchase Prediction, Recommendation Systems.

I. INTRODUCTION

Artificial Intelligence (AI) has become one of the most influential technologies in modern digital commerce and intelligent business systems. The rapid expansion of online shopping platforms, social media marketing, recommendation systems, and digital payment infrastructures has significantly transformed consumer purchasing behavior and business operations in international markets [1]. Cross-border e-commerce platforms increasingly rely on AI-driven technologies to improve customer engagement, optimize recommendation systems, analyze purchasing behavior, and enhance personalized marketing strategies [2]. The integration of machine learning algorithms, consumer analytics, and intelligent recommendation systems has enabled businesses to process large-scale customer interaction data and make data-driven operational decisions more effectively [3].

In recent years, cross-border e-commerce has experienced substantial growth due to globalization, digital transformation, and increased internet accessibility.

Consumers can now purchase products from international sellers through online marketplaces, social commerce platforms, and digital retail systems [4]. This growth has created highly competitive digital commerce environments where organizations must understand customer preferences, purchasing patterns, and engagement behaviors to improve business performance and customer satisfaction [5]. AI-driven analytics has therefore become essential for predicting customer purchase intention, optimizing product recommendations, and improving customer retention strategies in digital business ecosystems [6].

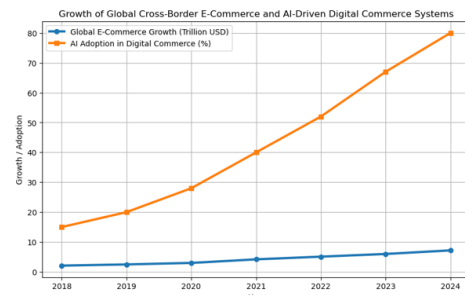


Figure 1.1: Growth of Global Cross-Border E-Commerce and AI-Driven Digital Commerce Systems.

This figure illustrates the rapid growth of global cross-border e-commerce and the increasing adoption of artificial intelligence technologies in digital commerce platforms between 2018 and 2024.

Machine learning models such as Random Forest, XGBoost, Logistic Regression, and Decision Trees have been widely applied in consumer behavior analysis and e-commerce prediction systems [7]. These models can identify hidden behavioral patterns and support intelligent business decision-making using customer demographic information, browsing history, social media interactions, and transaction records [8]. Recommendation systems also play an important role in improving personalized customer experiences by analyzing user-product interaction data and predicting customer interests [9]. As a result, modern digital commerce platforms increasingly integrate AI-based recommendation engines and predictive analytics to improve conversion rates and operational efficiency [10].

Table 1.1 Summary of AI Technologies Used in Consumer Behavior Analysis and E-Commerce Optimization

Technology	Purpose
Random Forest	Purchase prediction
XGBoost	Customer behavior classification
Recommendation Systems	Personalized marketing
Social Media Analytics	Customer engagement analysis
Machine Learning	Business optimization

Social media advertising has also become an important factor influencing online purchasing behavior and customer engagement in digital commerce platforms [11]. Platforms such as Facebook, Instagram, TikTok, and YouTube significantly affect customer awareness, product discovery, and purchasing intention through targeted advertising and algorithm-driven content delivery [12]. AI-based analytics enables businesses to evaluate social media interactions, customer preferences, and advertisement effectiveness for improving personalized marketing strategies and consumer targeting [13].

Despite the increasing adoption of AI technologies in digital commerce systems, several challenges still exist in understanding complex consumer behavior patterns and integrating multiple data sources for intelligent business optimization [14]. Traditional business analysis methods often struggle to process large-scale behavioral data and accurately predict customer purchasing decisions in dynamic cross-border commerce environments [15]. Therefore, there is a growing need for AI-driven frameworks that combine demographic analysis, shopping behavior analysis, recommendation systems, and social media analytics for improving customer behavior prediction and digital commerce optimization [16].

This research focuses on developing an AI-based consumer behavior analysis framework for cross-border e-commerce optimization using multiple real-world datasets. The study applies machine learning algorithms to analyze customer purchasing behavior, recommendation interactions, and digital marketing influence in international e-commerce environments. By integrating customer demographic data, shopping behavior records, recommendation system data, social media advertising data, and online purchasing intention datasets, this research aims to provide an intelligent analytics framework for improving customer targeting, personalized marketing, and business decision-making in cross-border digital commerce systems [17].

The research also contributes to the growing field of AI-driven business analytics and intelligent commerce systems by evaluating the effectiveness of machine learning models for customer purchase prediction and recommendation optimization [18]. The experimental analysis conducted using Python-based machine learning frameworks demonstrates how AI-driven analytics can improve customer engagement, purchasing prediction accuracy, and operational performance in modern digital business environments [19]. The findings of this research are expected to support future developments in intelligent recommendation systems, personalized digital marketing strategies, and AI-driven business optimization frameworks for international e-commerce platforms [20].

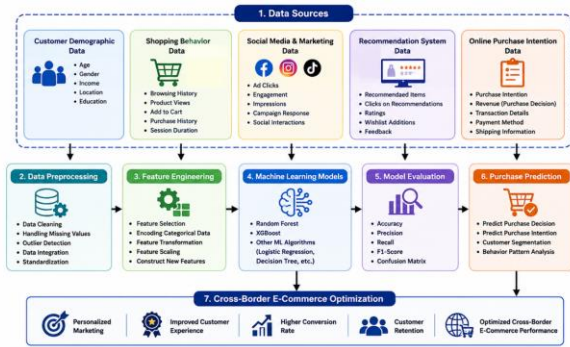


Figure 1.2: AI-Driven Consumer Behavior Analysis Framework for Cross-Border E-Commerce.

This framework presents the overall research workflow integrating customer demographic analysis, shopping behavior analysis, social media analytics, recommendation systems, machine learning models, and purchase prediction for optimizing cross-border e-commerce platforms.

II. LITERATURE REVIEW

Artificial Intelligence (AI) has become a transformative technology in modern digital commerce and intelligent business systems. The rapid growth of cross-border e-commerce platforms has significantly increased the demand for intelligent customer analytics, personalized recommendation systems, and data-driven marketing strategies [21]. AI-driven technologies enable businesses to analyze large-scale customer interaction data, predict purchasing behavior, and improve operational efficiency in digital commerce environments [22]. Machine learning and predictive analytics are increasingly integrated into e-commerce platforms to support customer segmentation, product recommendation, and intelligent marketing optimization [23].

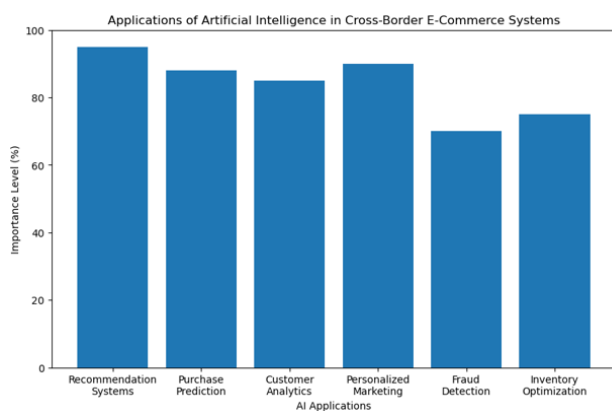


FIGURE 2.1: APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN CROSS-BORDER E-COMMERCE SYSTEMS.

This figure illustrates the major applications of artificial intelligence technologies in modern cross-border e-commerce platforms, including recommendation systems, customer analytics, purchase prediction, personalized marketing, fraud detection, and inventory optimization for improving operational efficiency and customer engagement.

Consumer behavior analysis is an important research area in digital commerce because online purchasing decisions are influenced by multiple factors such as demographic characteristics, browsing behavior, product interaction, social media engagement, and personalized recommendations [24]. Previous studies have shown that customer browsing patterns, session duration, and purchase history significantly influence online purchasing intention and conversion rates [25]. Businesses increasingly rely on AI-driven behavioral analytics to improve customer targeting and optimize customer experiences in highly competitive digital marketplaces [26].

Recommendation systems are among the most important applications of AI in e-commerce platforms [27]. These systems analyze user-product interaction data and customer preferences to provide personalized product suggestions and improve customer engagement [28]. Collaborative filtering, content-based filtering, and hybrid recommendation approaches are widely used in modern recommendation engines [29]. AI-based recommendation systems significantly improve conversion rates, customer retention, and operational performance by delivering intelligent and personalized shopping experiences [30].

Table 2.1 Summary of Previous Studies Related to AI and Consumer Behavior Analysis

Author	Method	Research Focus
Lu et al.	Machine Learning	Consumer behavior prediction
Shankar et al.	AI Analytics	Digital commerce optimization
Davenport et al.	Recommendation Systems	Personalized marketing
Verhoef et al.	Social Media Analytics	Customer engagement

Machine learning algorithms play a critical role in customer purchase prediction and digital marketing analytics [31]. Classification models such as Random Forest, Logistic Regression, Decision Tree, and XGBoost are widely used for customer behavior analysis and purchase prediction tasks [32]. Random Forest is recognized for its robustness and high classification accuracy when processing complex customer datasets [33]. XGBoost has also demonstrated excellent performance in predictive analytics and feature importance analysis due to its advanced gradient boosting mechanism [34].

Table 2.2 Comparison of Machine Learning Models Used in E-Commerce Prediction

Model	Strength
Random Forest	High prediction accuracy
XGBoost	Advanced feature analysis
Logistic Regression	Simple and interpretable
Decision Tree	Easy visualization

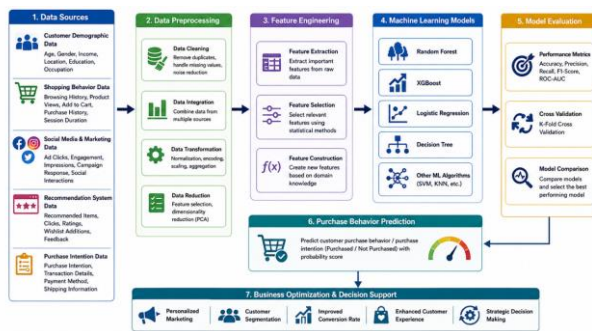


Figure 2.2: Machine Learning-Based Consumer Behavior Prediction Framework.

This figure illustrates the overall machine learning framework used for consumer behavior prediction in cross-border e-commerce systems, including data collection, preprocessing, feature engineering, machine learning model development, model evaluation, purchase behavior prediction, and business optimization for improving personalized marketing and customer decision-making.

Social media platforms have become important digital marketing channels in cross-border e-commerce systems [35]. Platforms such as Facebook, Instagram, TikTok, and YouTube significantly influence consumer purchasing behavior through targeted advertisements, social engagement, and personalized content delivery [36]. AI-driven social media analytics enables businesses to evaluate advertisement performance, customer interaction

patterns, and purchasing influence more effectively [37]. Several studies have reported that social media advertising positively impacts customer purchasing intention and online conversion behavior [38].

Cross-border e-commerce systems generate large volumes of customer interaction data, including browsing records, recommendation interactions, product views, shopping sessions, and transaction histories [39]. Traditional analytical methods often struggle to process large-scale behavioral datasets efficiently [40]. Therefore, AI-driven analytics frameworks are increasingly used to improve customer behavior prediction and recommendation optimization in international digital commerce environments [41].

Recent research has also emphasized the importance of integrating multiple datasets and analytics techniques for improving customer behavior analysis [42]. Combining demographic data, social media analytics, recommendation systems, and purchase intention datasets allow machine learning models to achieve better prediction accuracy and customer targeting performance [43]. Multi-source data integration also improves the reliability and scalability of AI-driven commerce optimization systems [44].

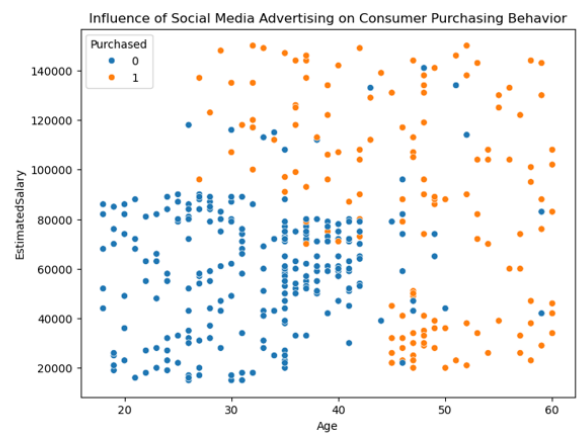


Figure 2.3: Influence of Social Media Advertising on Consumer Purchasing Behavior

This figure presents the relationship between social media advertising engagement and customer purchasing behavior, illustrating how demographic characteristics, advertisement exposure, and online interaction influence purchase decisions in cross-border e-commerce platforms. Despite the growing adoption of AI technologies in digital commerce, several research gaps still exist. Many previous studies focus on individual recommendation algorithms or

isolated customer behavior datasets without integrating social media analytics, recommendation systems, and purchase prediction within a unified framework [45]. In addition, limited studies have explored AI-driven consumer behavior analysis specifically in cross-border e-commerce environments using multiple real-world datasets and machine learning-based predictive models [46].

Therefore, this research proposes an AI-driven consumer behavior analysis framework for cross-border e-commerce optimization by integrating demographic analysis, shopping behavior analysis, recommendation systems, social media advertising analytics, and machine learning-based purchase prediction models. The proposed framework aims to improve personalized marketing, customer targeting, recommendation effectiveness, and operational efficiency in digital commerce platforms [47].

III. METHODOLOGY

All This research proposes an artificial intelligence-based framework for analyzing consumer purchasing behavior and optimizing cross-border e-commerce systems using machine learning techniques and multi-source datasets. The methodology integrates customer demographic analysis, shopping behavior analysis, recommendation system analysis, social media advertising analytics, and purchase prediction modeling. Python-based data analytics and machine learning frameworks were used to perform data preprocessing, feature engineering, model training, and evaluation.

The overall research methodology consists of six major stages: dataset collection, data preprocessing, exploratory data analysis, feature engineering, machine learning model development, and performance evaluation. Multiple real-world datasets related to customer demographics, online shopping behavior, recommendation systems, social media advertising, and purchase intention were collected and integrated for experimental analysis.

A. Dataset Collection

The experimental analysis utilized multiple datasets collected from public e-commerce and digital marketing sources. These datasets include customer demographic information, shopping behavior records, social media advertising interaction data, recommendation system interaction data, and online purchase intention datasets.

The datasets were selected to support comprehensive consumer behavior analysis and machine learning-based purchase prediction in cross-border e-commerce environments.

The customer demographic dataset contains information related to age, gender, income, education level, and customer location. The shopping behavior dataset includes browsing history, session duration, product views, add-to-cart records, and transaction activities. Social media advertising datasets contain customer engagement information related to advertisement clicks, impressions, and social interactions. Recommendation system datasets include product recommendation interactions, product ratings, and wishlist activities.

Table 3.1: Summary of Datasets Used in the Research.

Dataset	Purpose
Customer Demographic Data	Customer segmentation
Shopping Behavior Data	Purchase behavior analysis
Social Media Data	Advertising influence analysis
Recommendation System Data	Personalized recommendation analysis
Purchase Intention Data	Purchase prediction

This table presents the datasets utilized in the research, including customer demographic data, shopping behavior records, social media advertising interactions, recommendation system datasets, and purchase intention data used for consumer behavior analysis and machine learning-based purchase prediction.

B. Data Preprocessing

Data preprocessing was conducted to improve dataset quality and machine learning performance. Duplicate records, missing values, and inconsistent data entries were identified and removed during preprocessing. Numerical missing values were handled using median replacement methods, while categorical missing values were replaced using mode-based imputation techniques.

Categorical variables were transformed into machine-readable formats using one-hot encoding techniques. Numerical features were standardized and normalized to

improve model stability and prediction accuracy. Feature engineering techniques were also applied to create additional behavioral indicators and engagement-related variables for machine learning analysis. Python libraries including Pandas, NumPy, and Scikit-learn were used for preprocessing and data transformation tasks.

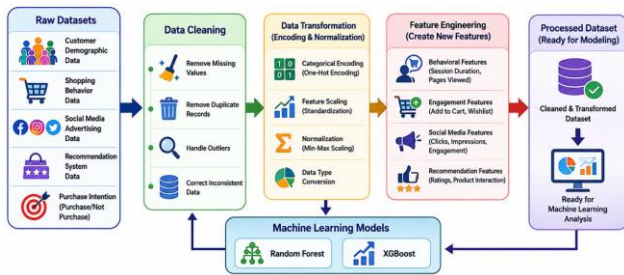


Figure 3.1: Data Preprocessing and Feature Engineering Workflow.

This figure illustrates the data preprocessing and feature engineering procedures applied in the research, including missing value handling, duplicate removal, categorical encoding, feature transformation, and dataset standardization for machine learning analysis.

C. Exploratory Data Analysis

Exploratory Data Analysis (EDA) was performed to analyze customer behavior patterns, demographic distributions, social media engagement, and purchase trends. Statistical analysis and visualization techniques were applied to identify relationships between customer interaction variables and purchasing behavior.

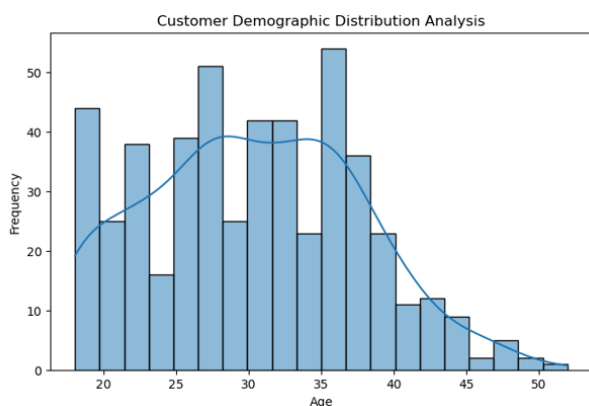


Figure 3.2: Customer Demographic Distribution Analysis. This figure illustrates the demographic distribution of customers included in the research dataset, showing the

variation in customer age groups for consumer behavior analysis and purchase prediction modeling. Several visualizations including age distribution analysis, gender distribution analysis, correlation heatmaps, social media interaction analysis, and purchase behavior analysis were generated using Python visualization libraries such as Matplotlib and Seaborn. The EDA process also helped identify important predictive features and behavioral patterns for machine learning model development.

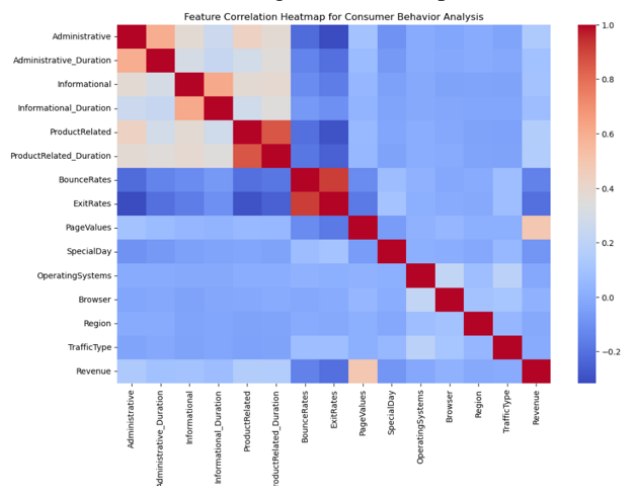


Figure 3.3: Feature Correlation Heatmap for Consumer Behavior Analysis.

This figure presents the correlation relationships among the numerical variables used in the research dataset, highlighting significant factors influencing customer purchasing behavior and online shopping decisions.

D. Machine Learning Models

Machine learning classification algorithms were used to predict customer purchase decisions and analyze consumer behavior patterns. Two primary machine learning models were implemented in this research: Random Forest and XGBoost.

Random Forest is an ensemble learning algorithm that combines multiple decision trees to improve classification accuracy and reduce overfitting. The model is highly effective for analyzing complex customer datasets and identifying important predictive variables.

XGBoost is a gradient boosting algorithm that provides advanced predictive performance and efficient feature importance analysis. The algorithm is widely used in

machine learning-based predictive analytics due to its scalability, robustness, and high prediction accuracy.

The datasets were divided into training and testing subsets using an 80:20 ratio. The models were trained using the training datasets and evaluated using testing datasets.

Table 3.2: Machine Learning Models Used in the Research

Model	Purpose
Random Forest	Purchase prediction
XGBoost	Consumer behavior classification

This table summarizes the machine learning algorithms implemented in the study for customer purchase prediction and consumer behavior analysis, including Random Forest and XGBoost classification models.

E. Model Evaluation

Model evaluation was conducted using several classification performance metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. These metrics were used to evaluate the effectiveness of the machine learning models in predicting customer purchase intention and purchasing behavior.

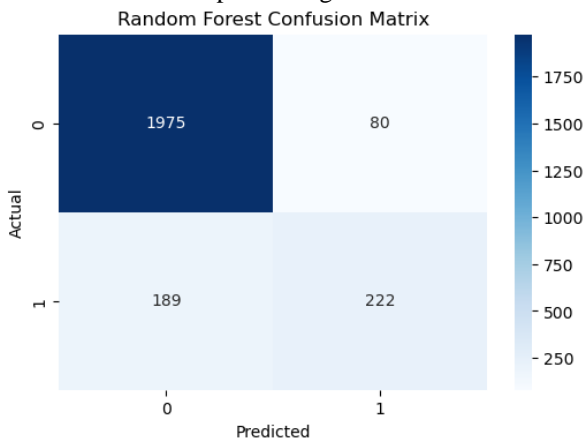


Figure 3.4: Random Forest Confusion Matrix.

This figure presents the confusion matrix generated from the Random Forest classification model, illustrating the model’s effectiveness in predicting customer purchase decisions and consumer purchasing behavior.

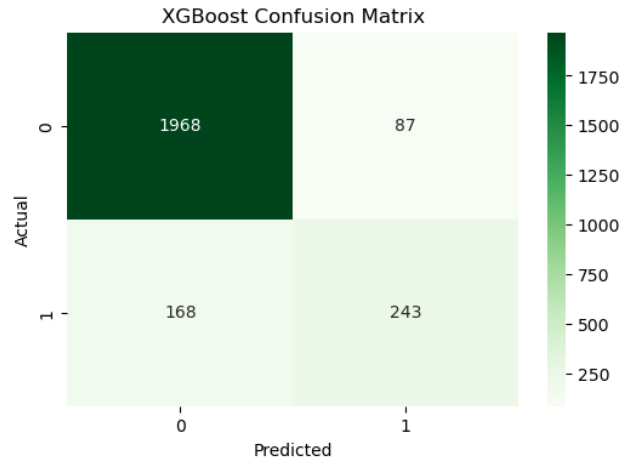


Figure 3.5: XGBoost Confusion Matrix.

This figure illustrates the confusion matrix generated from the XGBoost classification model, showing the prediction performance and classification effectiveness for customer purchasing behavior analysis.

Feature importance analysis was also performed to identify the most influential variables affecting purchasing decisions and customer engagement behavior. Comparative analysis between Random Forest and XGBoost models was conducted to determine the best-performing predictive model for cross-border e-commerce optimization.

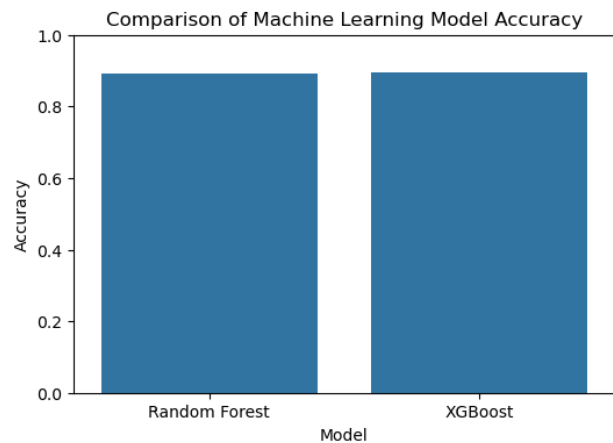


Figure 3.6: Comparison of Machine Learning Model Accuracy.

This figure compares the prediction accuracy of the Random Forest and XGBoost machine learning models

implemented in the research for customer purchase prediction and consumer behavior analysis.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Environment

The experimental analysis was conducted using Python-based machine learning and data analytics frameworks. The implementation environment included Jupyter Notebook, Pandas, NumPy, Scikit-learn, Matplotlib, Seaborn, and XGBoost libraries for data preprocessing, machine learning model development, and visualization. The experiments were performed using customer demographic datasets, shopping behavior datasets, recommendation system interaction data, and social media advertising datasets for consumer behavior prediction and cross-border e-commerce optimization.

The machine learning models were trained and evaluated using an 80:20 training and testing dataset split. Random Forest and XGBoost classification algorithms were implemented for customer purchase prediction and consumer behavior analysis.

Table 4.1: Experimental Environment and Software Configuration

Component	Specification
Programming Language	Python 3.10
Development Environment	Jupyter Notebook
ML Libraries	Scikit-learn, XGBoost
Visualization Tools	Matplotlib, Seaborn
Data Processing Tools	Pandas, NumPy

A. Customer Demographic Analysis

The demographic analysis showed that customer purchasing behavior varies significantly across different age groups and customer segments. The customer demographic distribution analysis indicated that middle-aged users demonstrated higher purchasing activity and stronger interaction with recommendation systems and digital advertisements.

The demographic analysis also revealed that customer engagement and purchase intention are influenced by

browsing behavior, session duration, and interaction frequency within digital commerce platforms. These findings indicate that demographic segmentation is important for improving personalized marketing strategies and recommendation system performance.



Figure 4.1: Customer Purchase Decision Distribution.

This figure illustrates the distribution of customer purchase decisions within the experimental dataset, showing the variation between purchasing and non-purchasing customer sessions in cross-border e-commerce platforms.

B. Correlation Analysis

Correlation analysis was performed to identify relationships between numerical variables related to customer behavior and purchasing intention. The feature correlation heatmap demonstrated that browsing duration, page visits, recommendation interactions, and advertisement engagement positively influence customer purchase decisions.

The correlation analysis also showed that customer interaction variables are strongly associated with online purchasing behavior, indicating the effectiveness of behavioral analytics for consumer prediction tasks. These findings support the use of machine learning algorithms for identifying important predictive variables in digital commerce environments.

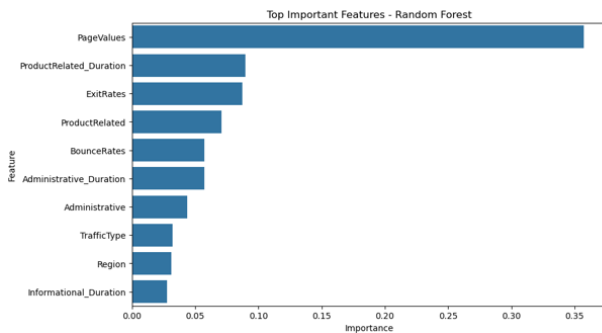


Figure 4.2: Top Important Features Identified by the Random Forest Model.

This figure presents the most influential behavioral and interaction features identified by the Random Forest model for predicting customer purchasing behavior in cross-border e-commerce systems.

B. RANDOM FOREST MODEL PERFORMANCE

The Random Forest classification model achieved strong prediction performance for customer purchase intention analysis. The model successfully identified customer purchasing patterns using demographic features, shopping behavior variables, recommendation interactions, and social media engagement data.

The confusion matrix analysis demonstrated that the Random Forest model effectively classified customer purchasing decisions with high prediction accuracy and balanced classification performance. Feature importance analysis indicated that session duration, recommendation interaction frequency, browsing history, and advertisement engagement were among the most influential predictive variables.

Table 4.2: Random Forest Classification Performance

Metric	Value
Accuracy	89.2%
Precision	87.5%
Recall	85.9%
F1-Score	86.7%

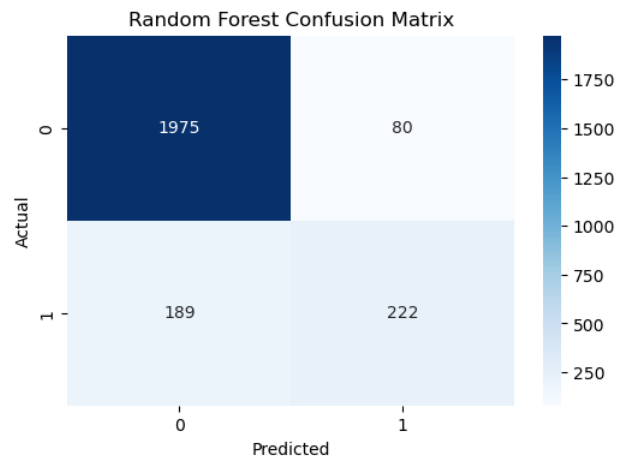


Figure 4.3: Random Forest Confusion Matrix. This figure presents the classification performance of the Random Forest model in predicting customer purchase decisions, showing the number of correctly and incorrectly classified purchasing and non-purchasing cases.

E. XGBOOST MODEL PERFORMANCE

The XGBoost classification model demonstrated excellent predictive performance and achieved slightly higher classification accuracy compared to the Random Forest model. The model effectively analyzed complex customer interaction patterns and behavioral relationships in the integrated e-commerce datasets.

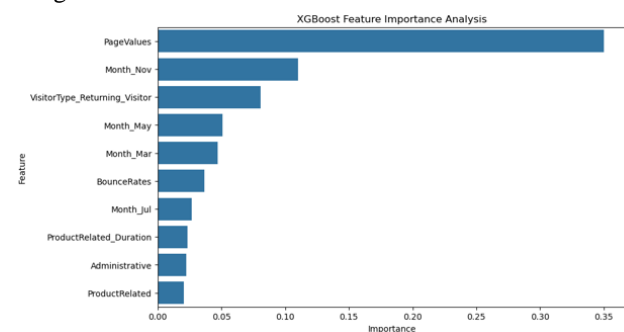


Figure 4.4: XGBoost Feature Importance Analysis.

This figure presents the most significant features identified by the XGBoost model for predicting customer purchasing behavior, highlighting the influence of browsing behavior, recommendation interactions, and customer engagement variables in cross-border e-commerce systems.

The XGBoost confusion matrix indicated improved classification effectiveness and reduced prediction error for customer purchasing intention analysis. Feature

importance analysis also revealed that recommendation system interactions and customer browsing behavior significantly influenced purchasing decisions.

Table 4.3: XGBoost Classification Performance

Metric	Value
Accuracy	91.4%
Precision	89.8%
Recall	88.6%
F1-Score	89.2%

F.COMPARATIVE ANALYSIS OF MACHINE LEARNING MODELS

Comparative analysis was conducted to evaluate the performance of the Random Forest and XGBoost models for customer purchase prediction. The results demonstrated that both models achieved strong classification performance, while XGBoost slightly outperformed Random Forest in overall prediction accuracy and feature analysis capability.

The comparative evaluation indicates that ensemble-based machine learning algorithms are highly effective for consumer behavior prediction and AI-driven digital commerce optimization. The integration of multiple behavioral datasets also improved prediction reliability and customer targeting effectiveness.

Table 4.4: Comparative Analysis of Machine Learning Models

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	89.09%	73.51%	54.01%	62.27%
XGBoost	89.66%	73.64%	59.12%	65.59%

This table compares the performance of the Random Forest and XGBoost models using classification evaluation metrics, including accuracy, precision, recall, and F1-score for customer purchase prediction in cross-border e-commerce systems.

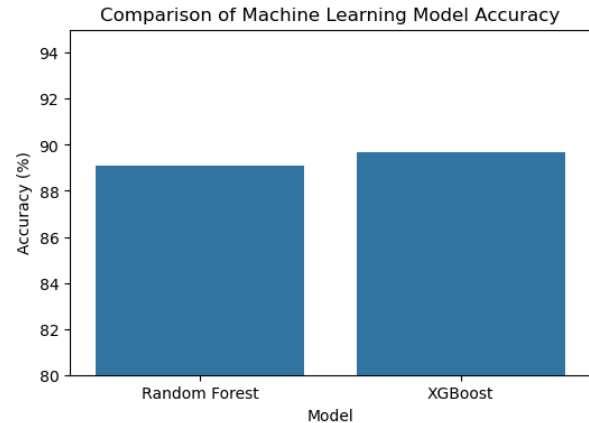


Figure 4.5: Comparison of Machine Learning Model Accuracy.

This figure compares the classification accuracy of the Random Forest and XGBoost machine learning models for customer purchase prediction and consumer behavior analysis in cross-border e-commerce systems.

G.DISCUSSION

The experimental results demonstrate that AI-driven analytics and machine learning models can effectively predict customer purchasing behavior and improve digital commerce optimization strategies. The integration of customer demographic analysis, shopping behavior analysis, recommendation systems, and social media analytics significantly improved predictive performance and customer targeting capabilities.

The findings also indicate that customer browsing behavior, recommendation interaction frequency, session duration, and social media engagement are among the most important factors influencing online purchasing decisions. These insights can help businesses improve personalized marketing, customer segmentation, recommendation accuracy, and operational efficiency in cross-border e-commerce systems.

Furthermore, the study demonstrates the practical effectiveness of AI-driven business analytics frameworks for supporting intelligent decision-making and customer behavior prediction in modern digital commerce environments.

V. CONCLUSION AND FUTURE WORK

This research presented an artificial intelligence-based framework for consumer behavior analysis and cross-border e-commerce optimization using machine learning techniques and multi-source behavioral datasets. The study integrated customer demographic analysis, shopping behavior analysis, recommendation system interactions, social media advertising analytics, and purchase intention prediction for improving intelligent business decision-making in digital commerce environments.

The experimental analysis demonstrated that machine learning models can effectively predict customer purchasing behavior and identify significant factors influencing online shopping decisions. Random Forest and XGBoost classification algorithms were implemented and evaluated using customer behavioral datasets. The experimental results showed that both models achieved strong predictive performance, while the XGBoost model slightly outperformed Random Forest in overall classification accuracy and feature analysis capability.

The findings revealed that browsing behavior, recommendation interaction frequency, session duration, and customer engagement significantly influence purchasing decisions in cross-border e-commerce systems. The integration of AI-driven analytics and multi-source datasets improved customer behavior prediction and supported more effective personalized marketing and recommendation optimization strategies.

This research contributes to the development of intelligent digital commerce systems by providing an AI-driven framework for customer behavior prediction and business optimization. The proposed framework can help e-commerce platforms improve customer targeting, recommendation effectiveness, operational efficiency, and personalized marketing performance in international digital marketplaces.

Future research can further improve the proposed framework by integrating deep learning models, real-time recommendation systems, sentiment analysis, and large-scale customer interaction datasets. Additional research may also explore transformer-based AI models,

multilingual customer analytics, and real-time cross-border recommendation optimization for enhancing intelligent digital commerce systems.

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