

The impact of Artificial Intelligence on E-commerce Customer Experience and Personalization

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Abstract: Businesses aim to provide clients with personalized recommendations in today's cutthroat market environment in order to boost engagement, retention, and income. Businesses are looking for creative ways to customize their marketing campaigns and content to each customer's tastes as a result of the development of artificial intelligence (AI). Machine learning (ML) models can forecast personalized recommendations for goods, services, and content by examining consumer behavior and interests. The objective of present investigation is to investigate how ML methods can be used to forecast e-commerce product on-time delivery, annual spending, and customer attrition. The research has demonstrated that a range of ML techniques, including as KNN, Navie Bayes, and gradient boosting, have been successfully used to forecast customer churn across many industries. The study used ML techniques to empirically analyses customer turnover in e-commerce in order to fill this vacuum in the literature. The results of the study show that ML methods are useful for forecasting customer attrition and product delivery in e-commerce. The top-performing algorithm, gradient boosting, predicted customer attrition with an accuracy of 90.67% and product on-time delivery with an accuracy of 73.75%.

Keywords: Artificial intelligence, Machine learning, Personalization, E commerce, Customer behavior.

I. INTRODUCTION

Businesses in a variety of sectors are putting more emphasis on improving the customer experience as a crucial difference for success in the current digital era. Personalized recommendations, which use machine learning algorithms to provide customized ideas to specific clients, are a potent tactic for accomplishing this goal. ML approaches are able to anticipate and recommend information, services, and goods that are most relevant and appealing to each individual customer by assessing large volumes of data about consumer preferences [1], behavior, and interactions.

One area of computer science is artificial intelligence. The range of applications for artificial intelligence is expanding as computer technology advances [2]. The client-side approach defines e-commerce as the process by which buyers and sellers

use the Internet as the network background to exchange goods and money as part of trade operations [3]. The application of artificial intelligence technology to e-commerce personalized advice is not well studied in current e-commerce research, which primarily concentrates on the study of its mode of operation [4].

The organizational structures of sales organizations are still undergoing major changes even in the era of e-commerce [5]. The advancement of information and communication technology had an impact on many facets of life, including the status of the economy.

The practice of buying or selling goods and services online using electronic media is known as e-commerce [6]. Hybrid sales structures that can handle online seller-buyer relationships and further leverage advancements in business intelligence and sales automation to improve sales performance have been created as a result of the shift from traditional, external sales forces to the concurrent use of inside sales personnel [7].

The core of personalized recommendation systems is machine learning, which enables them to evaluate enormous volumes of data and produce pertinent recommendations. Machine learning is essential for deriving significant insights and patterns from modern data because traditional rule-based systems are unable to handle its complexity and scale. Over time, ML techniques [8] can enhance suggestion accuracy, adapt to changing tastes, and reveal hidden correlations between things and people [9]. ML makes it possible for recommendation systems to provide individualized experiences on a large scale by utilizing methods such as collaborative filtering, content-based filtering, and hybrid approaches [10].

The purpose of the investigation is to investigate these elements in the context of online shopping and to pinpoint methods for enhancing revenue forecasting, on-time delivery, and client retention. The study will employ quantitative and qualitative research techniques, together with accurate data analysis, to accomplish this goal. The results of the study will aid in the creation of practical plans for lowering customer attrition, enhancing on-time delivery, and forecasting yearly e-

commerce expenditures. The study will give e-commerce businesses important insights into consumer behavior and assist them in customizing their marketing and sales tactics to match the demands and expectations of their clientele.

II. LITERATURE REVIEW

To investigate consumer intents to switch from traditional e-commerce to mobile commerce, studies created a model. The findings demonstrated that the model could properly predict consumers' readiness to switch from traditional to mobile e-commerce by leveraging the relationship between perception technology and value differences. [11].

Understanding and analyzing user preferences and behaviors in-depth in order to customize recommendations is the cornerstone of personalized recommendations. The first step in this process is gathering a variety of user data, including implicit signals like clicks and past purchases as well as explicit feedback like ratings and reviews. Because the system's items are represented in a feature space, it is possible to make insightful comparisons and predictions based on characteristics like popularity, genre, and category. From straightforward techniques like user-based collaborative filtering [12] to more intricate techniques like matrix factorization and deep learning models, user modelling is essential to creating user profiles.

AI is crucial for automating many marketing tasks, such as predictive analytics, customer relationship management, and content production, in order to maximize marketing tactics [13]. Research indicates that companies like Amazon and Netflix employ AI to improve consumer experiences and gain a competitive advantage in rapidly evolving marketplaces [14]. However, ethical issues including algorithmic biases and privacy concerns are also raised by the application of AI. Therefore, a well-rounded approach that prioritizes accountability and transparency is needed [15].

The study "Leveraging Artificial Intelligence in E-commerce: Enhancing Customer Experience and Improving Business Performance" was conducted by [16]. E-commerce is only one of the businesses that have been completely transformed by the introduction of AI. Recent years have seen an exponential growth in technology, which is now essential in almost every area of the economy. Indeed, it may be argued that contemporary companies simply cannot function without cutting-edge technology infrastructure. Significant changes occur in the business sector, especially when e-commerce is used, or even when e-commerce is not used solely, but rather in conjunction with the concept of artificial intelligence. One of the characteristics of artificial intelligence is its capacity to analyse and make inferences from vast datasets. This technology is already being used by the e-commerce sector to find patterns in data from a variety of sources, such as past browser activity, transactions, credit reports, and account information.

An acceptability model for e-commerce personalization technologies was put forth by some researchers. Comparative research showed that the framework could correctly identify the behavioral intention of customers using mobile applications for e-commerce and customized consuming, as well as

exposing consumers' concerns about privacy and self-willingness to control the connection among behavioral intention and e-commerce personalization [17].

Researchers conducted research an analysis of M-commerce's use of artificial intelligence as a result, the use of technology in services is increasing rapidly [18]. This is the essence of contemporary, personalized living. Customer service permeates every aspect of contemporary life, with different pop-ups symbolizing cutting-edge technology. The science and technology sector is experiencing tremendous innovation in response to customer preferences for both new products and mobile users. The retail sector also displays goods and services. It's interesting to watch a lot of changes. Everything is up for grabs, from intricate and indirect advertising to conventional physical shopfronts that sell goods created by different customers [19].

In order to study the dynamics of frequent e-commerce users in a particular nation, studies gathered data on these customers over time and suggested a random model. Employing a suitable probability density function, the resulting solution was able to convey data uncertainty at the precise instant when sample data became available [20].

III. METHODOLOGY

The recommended method diagram for customer analysis of data in e-commerce websites is shown in Figure 1. It comprises multiple procedures for customer attrition, customer yearly spending, and on-time delivery of product. First, three datasets were gathered then applied a few dataset preparation techniques. Following that, the customer churn dataset was classed according to whether or not it included samples of churn, and the datasets of on-time delivery of product were grouped according to whether or not they included samples of on-time delivery or on-time, not delivery. Following that, certain ML techniques are used to forecast on-time delivery

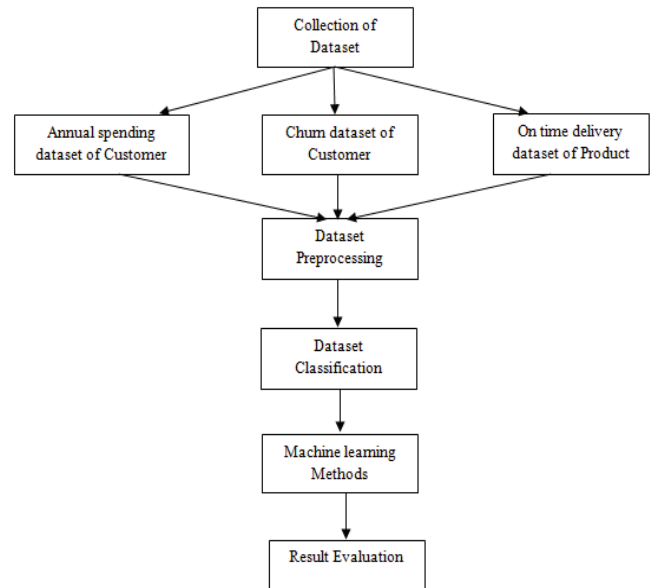


Fig. 1. Proposed framework

and customer attrition. Once the customer annual spending dataset has been prepared, make predictions using a ML approach called linear regression. The final phase involved analyzing the data for testing according to the dataset's parameters and comparing the effectiveness of the algorithm across all datasets using a few classification criteria.

A. Collection of Data

Three datasets that were gathered from the Kaggle website were utilized in this study to forecast and examine consumer data. These datasets, which include numerous attributes, include the customer churn dataset, the on-time delivery dataset of product and the customer annual expenditure dataset based on device usage.

Six criteria are used to categories the 6742 samples in the customer churn dataset as either churned or not. In order to obtain good results with the fewest possible parameters, this research used six of the sixteen parameters in the real dataset of churn that was gathered from the Kaggle. There are 547 samples and 5 parameters in the annual spending dataset, and 11,897 samples and 8 parameters in the on-time product delivery dataset of product, which are used to categories delivered and non-delivered samples.

B. Dataset Preprocessing

Data pre-processing is crucial to this study in order to increase the consistency and dependability of the datasets. Used a few pre-processing methods for the data. Because ML techniques only operate with numerical features and not categorical ones, it utilized the mean value for those data columns that had null or missing values. As a result, it used label encoding and one-hot encoding to transform numerical information from category-based information on those datasets.

C. Models for machine learning

After being pre-processed, datasets are prepared to be fed into algorithms that use machine learning for data analysis and prediction. Out of the three datasets, the data for test and train should be split into two groups. Set aside 20% of the data for testing and 80% for training in the annual spending and customer churn datasets. Furthermore, 75% of the on-time product delivery dataset was used for training and 25% was used for testing.

The sample size for each dataset, training, and testing is shown in Table I. Four popular machine learning algorithms— Gradient Boosting (GB), KNN, Navie Bayes (NB), and Decision Tree (DT) were used to forecast and analyses customer attrition and product on-time delivery. This study predicted the yearly spending of customers using the linear regression algorithm and analysis.

TABLE I. THREE DATASETS AND THE NUMBER OF SAMPLES

Dataset	Testing	Training	Total Dataset
Customer annual spending	151	396	547
Product on line delivery	3749	8148	11897
Customer Churn	1964	4778	6742

IV. EMPIRICAL RESULTS

Four machine learning techniques are applied to the customer churn dataset in this study, using specific variables that are detailed before. Table II shows the outcomes of all models. This paper selects an algorithm that achieves a modest accuracy difference among train and test data in order to prevent overfitting problems if we examine the customer churn dataset's performance measures. The gradient boost approach has superior precision, recall, and F1-score values and has a smaller accuracy gap between test and train data than other algorithms. Obtain the greatest test data accuracy of 90.67% as well. Out of the four algorithms, the Gradient Boost algorithm produces the best results.

TABLE II. ALL MODELS' PERFORMANCE METRICS ON THE CHURN DATASET OF CUSTOMER

Methods	Precision	Recall	F1 score	Accuracy
KNN	86.57	89.01	80.25	89.86
Navie Bayes	87.63	90.21	81.37	90.42
Gradient Boosting	91.53	90.56	80.24	90.67
Decision Tree	85.36	88.35	84.12	88.94

Figure 2 depicts the graphical representation of performance matrix on the Churn dataset of Customer.

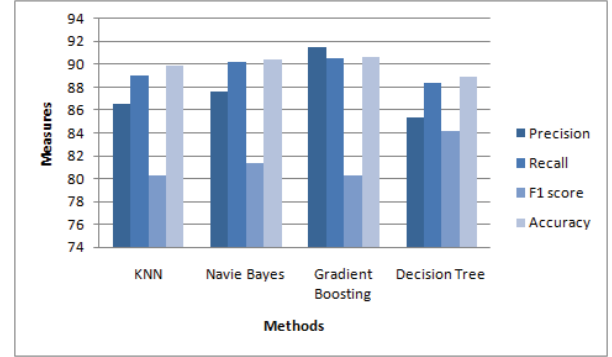


Fig. 2. Graphical representation of performance matrix

This paper applied the linear regression technique to the customer yearly expenditure information, and Table III displays the algorithm's performance outcomes. The R2_score values for the test and train data are .937 and 0.9547, respectively, and both are near to 1. The MAE, MSE, and RMSC values are all reasonable. Accordingly, the customer annual expenditure dataset is thought to be a good fit for the linear regression algorithm.

TABLE III. PERFORMANCE OUTCOMES OF THE ANNUAL SPENDING DATASET FOR CUSTOMERS

Methods		Linear Regression
Train	MAE	8.67
	MSE	91.38
	RMSC	10.65
	R2 score	.9547
Test	MAE	9.68
	MSE	121.85
	RMSC	11.75
	R2 score	.9371

The on-time delivery of product dataset is employed in the present study to train four ML techniques; every method is given specific variables that are explained above. Table IV displays each model's measures of performance. While the Gradient boost technique produces 73.75% accuracy of data from testing, which is the closing number, the Navie Bayes approach produces 73.79% test data accuracy. However, compared to other algorithms, the Gradient boost approach has a smaller accuracy differential between test and train data. Obtain high F1_score, precision, and recall scores. Consequently, the Gradient boost technique of Gradient boost produces the best results for the on-time product delivery dataset out of these four methods, which motivates us to implement it for analysis and prediction on the e-commerce site.

TABLE IV. ALL MODELS' PERFORMANCE METRICS ON THE DATASET OF ON-TIME DELIVERIES

Methods		KNN	NB	GB	DT
Train	Precision	77.89	84.46	83.35	99.9
	Recall	70.02	75.86	74.64	99.9
	F1 score	70.02	74.47	73.34	99.9
	Accuracy	81.26	74.17	73.81	99.9
Test	Precision	76.83	80.54	82.65	71.79
	Recall	71.46	73.52	73.52	70.32
	F1 score	71.46	73.52	73.21	70.32
	Accuracy	72.18	73.79	73.75	69.89

Figure 3 shows the graphical representation of used methods performance metrics on the dataset of on time deliveries.

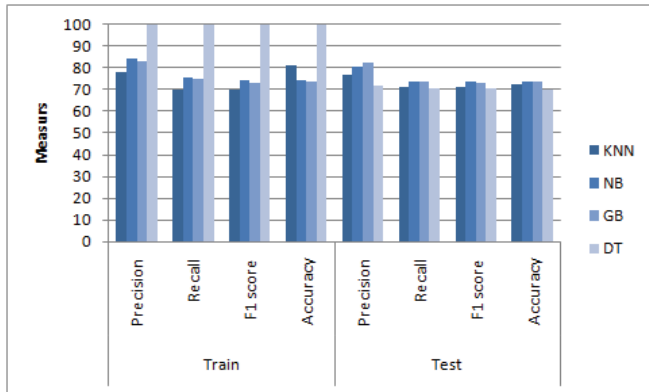


Fig. 3. Graphical representation of performance evaluation of on time deliveries

V. CONCLUSION

Personalized recommendations are becoming increasingly crucial as the e-commerce sector grows. Methods of ML can be used by businesses looking to increase revenue and client retention to predict annual consumer expenditure, customer attrition, and on-time delivery of product in the e-commerce industry. The outputs of this investigation show that consumer data may be analyzed efficiently using regression and classification algorithms. The study also discovered that in e-commerce, variables including average session duration, product categories, and frequency of purchases are significant

predictors of annual spending, customer attrition, and on-time delivery of product. The findings of this study can help advance knowledge of behavior of consumer in the e-commerce sector and offer suggestions for enhancing revenue and client retention.

Future directions for recommendation systems include explainable AI methods, context-aware suggestion development, and interaction with new technologies. By tailoring recommendations according to situational elements including time, place, and user context, context-aware recommendations seek to provide more timely and pertinent ideas. With its ability to handle complicated data, provide customized shopping services, and facilitate speedier client interaction, AI in eCommerce is reshaping the commercial landscape. Research indicates that more people are interacting with e-commerce companies, which helps firms raise their revenue.

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