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Predicting Customer Behavior Using Machine Learning and Deep Learning: A Comprehensive Review

Shivani Chouhan[1], Srashti Thakur[2]
Lakshmi Narain College of Technology, Indore (MP)[1, 2]
shivanichouhan0121@gmail.com[1], chouhansrashti00knw@gmail.com[2]

Abstract: *Understanding customer behavior is crucial for businesses aiming to enhance customer satisfaction, predict churn, and deliver personalized experiences. Recent advancements in machine learning (ML) and deep learning (DL) have significantly transformed the way organizations analyze and forecast customer actions across domains such as e-commerce, finance, and social media. This study presents a comprehensive review of contemporary approaches employed to predict and analyze customer behavior using various ML algorithms like Decision Trees, Random Forest, Logistic Regression, Support Vector Machines, Gradient Boosting, Naïve Bayes, and advanced DL models including Long Short-Term Memory (LSTM) and Transformer-based networks. The reviewed works demonstrate the use of large-scale structured and unstructured datasets, applying models for tasks such as churn prediction, sentiment analysis, product recommendation, and trend forecasting. The review also identifies the growing significance of social media analytics, ethical concerns related to data use, and the superior performance of ensemble and deep learning models in capturing customer intent. By synthesizing these findings, this paper highlights the state-of-the-art in predictive customer behavior modeling and suggests future directions for more interpretable, privacy-conscious, and context-aware intelligent systems.*

Keywords: *Customer Behavior Prediction, Machine Learning, Deep Learning, Customer Churn, Sentiment Analysis, Recommendation Systems, LSTM, Transformer, Social Media Analytics, Data Mining, Predictive Modeling, Consumer Analytics.*

1. INTRODUCTION

Sentiment analysis, natural language processing (NLP) methods, and computational linguistics can be used to find and remove subjective information from text. Reviews, polls, social media, and other ways let customers express their feelings and ideas. People also use healthcare media to share their thoughts and feelings. Sentiment analysis is a broad term that refers to how a person or group of people feel about a certain issue or situation in a given event, discussion, forum, interaction, or paper, for example. Sentiment Analysis can be used to figure out how text is polarised at the feature, phrase, and document level. As people want to share their thoughts on a variety of platforms, more people are using the Internet. This has led to an overflow of opinionated content on the Internet. A tool called sentiment analysis can be used to look at this data and get useful information that will help other people make decisions. There are many things you can find on the internet, like movies, airline reviews, and other types of social media data. It's also important to look at other types of data, such as news and publications, as well as the work done by staff. This is called "sentiment analysis." It's when you look at a piece of text and try to figure out what the person's feelings are. Social media platforms like Twitter, Facebook and Linkdin have given customers a new way to say what they think about goods, people, and places, and how they think they should be made. The only type of feedback that users can give is text. Many text messages are sent through social media and online shopping sites every day. The job of looking at and analysing the mood of the public is very important. NLP with artificial intelligence skills and text analytics can be used to figure out how negative, neutral, or positive a person is. Opinion mining and sentiment analysis can be done in any field or on any platform. This technology has become more common because of its many different applications, which have led to the growth of many businesses and organisations in a wide range of industries, such as social media, health care, management, and the economy.[1-2] Sentiment analysis can be used to make smart decisions as well as give business information. When you do opinion mining, there are two ways to do it: sentiment analysis and sentiment classification. People often use them together, even though they each have different properties. The use of sentiment classification lets you group a document or part of a document based on how it makes you feel. Sentiment orientation is a type of text classification that uses the sentiment orientation of opinion to group text. Feeling orientation is determined by how subjective it is, and this affects how the opinion turns out. Subjective analysis can be used to figure out whether text or review data is subjective or objective. In this study, we looked at a few different ways to figure out how people feel. It doesn't matter how many papers have been written on this subject. There is always a need to improve sentiment analysis accuracy and understanding. Sentiment analysis can be used in a lot of different ways. There's only one problem: human language is so hard to understand. There are many different ways to say this, including grammatical and cultural differences. An easy-to-understand sentence: "My order has been put back." "Did better than expected." The machine may not be able to understand. In some cases, "thin" is a good way to describe a laptop, but it can also be a bad way to describe a wall in an apartment. In order to get the most accurate results, sentiment analysis needs to be tailored to the needs of the organisation. E-commerce is becoming more common these days. Online shopping is becoming more popular than buying things in stores. The opinions and ratings of customers can be used to verify and publicise a product in the world of e-commerce and other online stores. These ratings and reviews help customers decide if they want to buy a product or not. This kind of content could have good or bad feedback from customers. [3]

Factors Affecting Customer Behavior

Customer behavior is influenced by a wide range of factors, which can be broadly categorized into psychological, personal, social, and cultural domains. Understanding these factors is essential for developing accurate predictive models and personalized customer strategies:[4]

1. **Psychological Factors**

- **Motivation**: Customers are driven by specific needs or desires that guide their decision-making.
- **Perception**: The way customers interpret information influences how they respond to marketing messages.
- **Attitudes and Beliefs**: Long-standing opinions or beliefs about a brand or product can significantly affect buying behavior.
- **Learning**: Prior experiences or exposure to marketing campaigns impact future decisions.

2. **Personal Factors**

- **Age and Life Stage**: Preferences change with age, income level, family size, and stage in life.
- **Occupation and Economic Status**: These define spending capacity and product preferences.
- **Lifestyle and Personality**: Individual habits, hobbies, and personality traits shape customer choices.

3. **Social Factors**

- **Family**: Family members often influence buying decisions, especially in household-related purchases.
- **Social Groups**: Friends, colleagues, and peer networks can impact trends and preferences.
- **Roles and Status**: A customer’s position in society or within a community can shape their behavior and brand choices.

4. **Cultural Factors**

- **Culture**: Values, beliefs, and customs passed down through generations play a major role in behavior.
- **Subculture**: Regional, religious, or ethnic groups have distinct purchasing patterns.
- **Social Class**: Purchasing power, tastes, and preferences often differ across socioeconomic strata.

5. **Technological and Digital Influence**

- **Online Reviews and Ratings**: Digital feedback significantly sways decisions.
- **Social Media Influence**: Platforms like Instagram, YouTube, and Twitter affect brand awareness and loyalty.
- **Personalization Algorithms**: Recommender systems and targeted advertisements shape user journeys.

6. **Situational Factors**

- **Purchase Occasion**: Special occasions often trigger unique buying patterns.
- **Availability and Convenience**: Ease of access, delivery speed, and stock availability influence choices.
- **Pricing and Offers**: Discounts, deals, and value-for-money perceptions impact final decisions.

Machine Learning Approaches

Many methodologies may be used to classify and forecast public opinion. Two of the most extensively used technologies for opinion mining and prediction are machine learning and lexicon-based methods. Furthermore, a hybrid technique that combines machine learning and lexicon-based approaches have been widely used [4] It improves the outcomes. The machine learning approach relies heavily on classification and text analysis. Text pre-processing is required to achieve the goal of text analysis, which is to make business judgments and strategic moves. To train a model that may be used to predict on a new set of data without labels, some data must first be collected. The two machine learning techniques are further classified into the following.

- Supervised Learning: From a tagged training dataset, supervised learning finds patterns and correlations.
- Unsupervised Learning: When a dataset is not labeled, unsupervised learning may be used to infer patterns from it.

Opinions can be classified based on how the text is handled. We'll go through a handful of them right now. There are numerous methods to categories the material, including at the sentence level. The viewpoint of each sentence is examined using sentence level classification. Each phrase is assumed to have a single point of view. When the aim is to analyze more than one point of view in a text, sentence-level classification is required. ‘Furthermore, sentences are classified in a distinct manner.

Another level of classification is termed document-level categorization when attempting to categories the perspective of an entire document. As a result, it is not suitable when a work has many points of view [5]The approach is unworkable since it is possible for a document to have more than one viewpoint, making document classification impossible.

Opinions may also be classified using user-level opinion analysis. This isn't a usual occurrence, but the researchers used it to investigate how a nearby user behaved. [6].'s major objective was to assess consumer connectedness using user-level sentiment analysis based on social media data. Aside from that, they sought to see if customers' views of connectedness altered as a result of the study.

The classification of aspects is another level of categorization. Using this method, product traits and attributes are highlighted in a phrase. For example, in the statement "The speaker of the mobile is excellent," the speaker serves as a foundation for making a decision. To complete the level, each sentence in a phrase can be utilizing d. The first two phases in the process are to identify the intended audience and obtain their feedback. The topic of the previously indicated level is the paper, paragraph, or sentences. Once you've discovered the difference between two words with opposing meanings, you may go on to determining how other individuals are feeling. When a product or service is the main focus, aspect level classification is frequently viewed as the ideal strategy. The models employed for opinion mining and product analysis, according to [7], are based on as-pect level classification. According to client input, product qualities may be extracted using the aspect level classification procedure, as illustrated in Figure 3. The models collect the qualities of the things that the reviewer has determined should be included in the feature selection. **[8]**

Product reviews

The increased usage of electronic commerce has resulted in a flood of data that must be analyzed in order to make educated decisions and complete pertinent activities. Because there is no formal reputation system in place, consumers are unfamiliar with items, features, and quality in digitally mediated marketplaces, and there are trust difficulties as a result of virtual connection. To compensate for the lack of confidence and quality in digitally managed marketplaces, consumers in digitally controlled markets might grade items based on the degree of expectation they meet. It is the consumer's responsibility to convey his or her ideas and explain whether or not the goods matched his or her expectations. The capacity of consumers to exchange knowledge about the quality of a product might assist alleviate customer uncertainty [9]. The capacity of a buyer to learn about a product's specifications, as detailed in reviews, may be a crucial component in their purchase decision. Researchers have identified customer assessments as an unresearched topic that might benefit other customers in their decision-making process.

What the organization needs to know is why customers would trust information provided by strangers, as well as how trust might be established in the consumers themselves. Credibility is a vital component of information sharing, and it has a big influence on product sales since it encompasses consumers' trust and reliability. Customers can not only write reviews on Amazon, but they can also vote on whether or not the input of other customers is valuable. If consumers agree with a reviewer's assessment, the voting provides a clear direction and a path for decision-making through the counts. The vote of helpfulness is an indicator of the quality of evaluations for other customers [10]. Reviews that include helpful votes considerably affect a customer's decision-making process, and these reviews have a higher impact on the sales of lesser-known goods than they do on more well-known ones.

Review mining

Data collection is an essential component of every type of investigation. Previously, researchers obtained reviews from databases or a URL provided by the firm. A web crawler is frequently used to collect data automatically. [11] Collected data using a custom web crawler and stored it in a local database. Utilize d the crawler to divide a huge work into smaller tasks and perform them in parallel.

Amazon assessments simply offer a product code and a quick overview in the absence of a thorough explanation of a product's attributes. It's difficult to gain relevant information about a product from reviews if the information supplied is incorrect. Consumers aren't expected to understand every detail of a re-product view's description. Aside from linguistic and emotional research, it is vital to uncover the characteristics of the product that are enticing customers to buy. Some of the reviews convey anything directly about the product, while others provide characteristics that a reviewer addresses. Product qualities are frequently described using nouns and phrases. As a feature, an attribute of the subject or an attribute of the subject's part must be retrieved. In the review, product features may be mentioned explicitly4 or implicitly is the year. Explicit qualities can be extracted manually or automatically. The features can be manually extracted by creating a vocabulary for qualities related to the product feature and then extracting those features from reviews. As a consequence, the data is divided into a number of unique classes, which are subsequently extracted.

Customer Satisfaction

When a customer is pleased with a product or service, it implies that the product met their expectations. To comprehend customer satisfaction as a pattern of elements and related sensations, we must first recognize that customer pleasure is based on the characteristic of the product or service under consideration. Customers are pleased when their needs are addressed. A product that surpasses consumers' expectations satisfies their desires.

A consumer can submit feedback in the form of text as well as by rating the product. A lower rating indicates dissatisfaction, whereas a higher one indicates contentment. A product rating is one of the most significant ways to assess a customer's level of satisfaction. One of the greatest methods to determine how happy a consumer is with a product is to assign ratings to it [12]. A product rating cannot be used to assess quality because it is a statement of client satisfaction. The study of customer happiness, which measures the contentment of each individual consumer, is the fundamental notion in marketing research [13]. When it comes to customer satisfaction (CS), it all boils down to the customer's expectations and the performance of the product.If a product has the ability to positively effect a consumer, the customer's expectations may be hypothesised as the probabilities of this occurring. Expectations cannot be idealized as a post-purchase occurrence since they are a pre-purchase phenomenon, but the customer implements them after viewing the goods.

Figure 1: Word Cloud of Amazon reviews

Unstructured data provides information on consumers' opinions and experiences, product highlights, product feature highlights, and other services such as product delivery, packaging, and other pertinent difficulties. Customers also give input on how a product or service should be improved, which includes their personal experiences. This data may also be utilize d to improve the product or service and create marketing plans. [19] predicted customer happiness by exploiting the technological characteristics of online reviews and comments, as well as consumer interaction in an online community, to predict customer contentment. As a result, a number of essential concerns must be addressed in order to link product ratings with review material. The reviews describe technical issues (features), which explain the variance in product ratings. Customer ratings based on attributes or features can have a significant influence [20]

2. LITEARTURE REVIEW

GhorbanTanhaei et al. (2024) developed a predictive customer relationship management framework using several machine learning algorithms such as Decision Tree, Random Forest, Logistic Regression, Support Vector Machines, and Gradient Boosting. Their model evaluated customer behavior using metrics like accuracy, recall, F1-score, and ROC-AUC. Random Forest and Logistic Regression outperformed the rest, achieving high precision and recall. The study emphasized the practical value of linking client portfolios with expenditure patterns to guide strategic marketing decisions [14].

Prakash et al. (2023) presented a comprehensive literature review exploring how AI-driven techniques like machine learning, natural language processing (NLP), and deep learning are used to predict consumer behavior. The study covered applications such as recommendation engines, sentiment analysis, and market forecasting while identifying key challenges like data privacy, ethical concerns, and system integration. The work laid the foundation for future research in AI-based consumer behavior prediction [15].

Kothari et al. (2024) proposed a novel Machine Learning-based Customer Behavior Model (MLbCBM), which integrates Logistic Regression, Decision Tree, Random Forest, KNN, SVM, and Naïve Bayes algorithms. The model demonstrated high accuracy rates (up to 89.9%) across various classifiers. It uses data collected from e-commerce platforms to detect emerging customer behavior patterns and facilitate decision-making through a server-based processing framework [16].

Basal et al. (2025) focused on predicting customer churn in subscription-based services using machine learning models like Random Forest, Logistic Regression, Gradient Boosting, and XGBoost. They employed Kaggle datasets and evaluated performance using confusion matrices and other metrics. The study particularly emphasized ethical considerations in predictive analytics and recommended targeted retention strategies and integration of new data sources to reduce churn rates [17].

Babu et al. (2025) introduced a novel application of the Reformer (Reversible Transformer) model to analyze massive social media datasets and predict customer sentiment and industry trends. Their study, particularly relevant for smart transportation and logistics, demonstrated that the Reformer outperformed traditional models in accuracy and efficiency. The work highlighted the growing role of social media analytics in real-time strategic business decisions [18].

Chaudhuri et al. (2021) aimed to improve the understanding of online consumer purchasing behavior through deep learning. By analyzing over 50,000 multidimensional web sessions, they evaluated the predictive power of deep learning against traditional ML models like Decision Tree, Random Forest, SVM, and ANN. Their findings showed that deep learning methods yielded superior results, making them suitable for predicting user behavior on e-commerce platforms [19].

Dhiman et al. (2024) analyzed Twitter data using Logistic Regression and Multinomial Naïve Bayes to uncover patterns in consumer behavior. Their model achieved a 92% prediction accuracy and emphasized the importance of analyzing language, emotion, and context in tweets. This study demonstrated the utility of social media data for marketing and decision-making, showcasing the potential of machine learning for behavioral trend detection [20].

Kurat et al. (2024) explored how predictive analytics and various machine learning techniques—such as supervised, unsupervised, and deep learning—can enhance market analysis. The study focused on demand forecasting, price optimization, and preference pattern identification using large datasets. It also addressed challenges like data quality and algorithmic bias, concluding that ML-driven analytics significantly improve strategic decision-making and business responsiveness [21].

Ojika et al. (2024) proposed a conceptual ML framework to analyze e-commerce trends and customer behavior. The framework includes advanced analytics like segmentation, sentiment analysis, recommendation systems, and predictive modeling. The goal was to increase customer engagement and conversion rates through data-driven marketing strategies, while acknowledging implementation challenges and suggesting future research directions [22].

Elamin et al. (2024) introduced a Bayesian-optimized Long Short-Term Memory (LSTM) model to predict media consumption behavior. By integrating Bayesian optimization with LSTM networks, the model achieved superior accuracy over other ML approaches such as Random Forest, RNNs, and Gradient Boosting. This study provided a robust methodology for modeling sequential behavior in rapidly evolving media consumption environments [23].

Chaudhary et al. (2021) investigated consumer behavior on various social media platforms using big data analytics. They collected diverse, high-speed data from Facebook, Twitter, LinkedIn, and others, and used machine learning to build predictive models. The research involved comprehensive preprocessing to clean the data and used predictive analytics to understand user engagement and perception on social platforms [24].

Jamal et al. (2024) conducted a qualitative study analyzing how AI—specifically machine learning and natural language processing—affects marketing strategies and customer behavior prediction. By reviewing over 60 publications and case studies, the study highlighted AI's role in enhancing marketing precision while addressing challenges related to data quality, integration, and security. Recommendations included improving AI talent and embedding AI into existing platforms for better strategic outcomes [25].

Khan et al. (2025) examined the impact of packaging design on consumer decisions related to educational toys using neuromarketing and machine learning. Their model analyzed which parts of the packaging drew customer attention using eye-tracking and other behavioral indicators. The study revealed that visual elements significantly influence purchasing decisions and emphasized the importance of social and contextual factors [26].

Juárez-Varón et al. (2020) explored online purchase prediction using a dataset of over 50,000 web sessions. The study identified platform engagement and customer attributes as the two main predictors of purchase intent. Comparing multiple ML techniques, including DT, SVM, RF, and ANN, they found deep learning to outperform the others. The research offered insights valuable for e-commerce development and academic advancements in consumer analytics [27].

Nisha et al. (2023) conducted a similar study to Juárez-Varón et al., using the same dataset to examine customer buying behavior on e-commerce platforms. They compared traditional ML models (DT, SVM, RF, ANN) with deep learning methods and concluded that deep learning models delivered better performance. The results provided meaningful insights for online retail platforms to optimize user engagement and sales forecasting [28].

Agrawal et al. (2021) focused on customer churn prediction in the telecom industry using a deep learning approach. They developed a multi-layered neural network model using features related to customer behavior, service usage, and support history. Achieving an 80.03% accuracy, the model helped identify high-risk churn customers and allowed companies to understand churn causes and improve customer retention strategies [29].

Table 1: Literature Review Table: Predictive Analytics & ML for Customer Behavior

Author(s)	Year	Objective	Methods / Models Used	Dataset / Source	Key Results	Contribution
GhorbanTanhaei et al.	2024	Forecast customer actions and support CRM	DT, RF, LR, SVM, Gradient Boosting	Client spending behavior data	RF & LR: High ROC-AUC (0.878), F1 (0.766), Recall (1.0)	ML for strategic CRM with model-based customer segmentation
Prakash et al.	2023	Review AI in customer behavior prediction	ML, NLP, Deep Learning	Literature & case studies	-	Broad overview of tools and challenges (ethics, privacy)
Kothari et al.	2024	ML-based Customer Behavior Model (MLbCBM)	LR, DT, RF, KNN, SVM, NB	E-commerce platforms	RF (89.9%), SVM (88.8%), NB (88.6%)	Server-based model analyzing market behavior
Basal et al.	2025	Predict churn in subscription services	RF, LR, GB, XGBoost	Real-world & Kaggle datasets	Accurate predictions; ethical focus	Actionable churn prediction framework with evaluation metrics
Babu et al.	2025	Use Reformer for social media-based insights	Reformer (Reversible Transformer)	Social media datasets	Superior precision, F1, recall	Applied NLP for market trends and demand prediction
Chaudhuri et al.	2021	Predict e-commerce purchases	DL, DT, RF, SVM, ANN	50K+ web sessions	DL outperformed ML	Showed DL strength in modeling purchase behavior
Dhiman et al.	2024	Predict consumer trends from Twitter	LR, Multinomial Naïve Bayes	Twitter data	92% accuracy	Trends from tweets support marketing decisions

Kurat et al.	2024	Market forecasting using ML & predictive analytics	DL, Supervised & Unsupervised ML	Real-time & historical market data	Predictive accuracy for demand & pricing	ML enables real-time adaptive market strategies
Ojika et al.	2024	Conceptual ML framework for e-commerce	Sentiment Analysis, Clustering, Predictive Modeling	Multi-source data	Improved engagement, conversions	Comprehensive ML-enabled business decision system
Elamin et al.	2024	Forecast media consumption	Bayesian-optimized LSTM	Media consumption datasets	99% accuracy (better than RF, GB)	Enhanced temporal modeling using Bayesian tuning
Chaudhary et al.	2021	Predict behavior from social media use	Big Data + ML	Facebook, Twitter, YouTube, etc.	High-quality results via preprocessing	Forecasted user interaction trends on social platforms
Jamal et al.	2024	AI's effect on marketing strategy	ML, NLP, Literature Analysis	60+ studies, cases	-	Identified AI benefits, risks in marketing and advertising
Khan et al.	2025	Study packaging influence on purchase	ML + Neuromarketing	Eye-tracking experiment data	Visual elements influence decisions	Segmented packaging zones via behavior analysis
Juárez-Varón et al.	2020	E-commerce purchase prediction	DL, DT, RF, SVM, ANN	50K+ web sessions	DL superior in predictions	Aid for platform development & user profiling
Nisha et al.	2023	Predict e-commerce behavior	DL vs ML (DT, RF, SVM, ANN)	Web session dataset	DL outperforms ML	Improved online purchase forecasting
Agrawal et al.	2021	Predict telecom customer churn	Deep Neural Network	Telco churn dataset	80.03% success rate	Identified key churn drivers with actionable insights

3. CONCLUSION

The prediction and analysis of customer behavior have become essential for organizations aiming to retain customers, personalize services, and enhance business outcomes. Through this review, it is evident that machine learning and deep learning techniques offer powerful tools for understanding complex patterns in customer data. Traditional algorithms like Decision Trees, Logistic Regression, and Random Forest continue to provide valuable insights, particularly when combined with ensemble techniques. However, the rise of deep learning models such as LSTM and Transformer architectures has significantly advanced the field by enabling the modeling of sequential and unstructured data with higher accuracy. Social media analytics, sentiment analysis, and customer churn prediction have emerged as key applications. Despite these advances, challenges remain in terms of interpretability, data privacy, and the need for domain-specific model tuning. Future research should focus on developing more explainable AI models, improving real-time prediction capabilities, and integrating ethical frameworks for responsible data usage. Ultimately, a hybrid approach that balances traditional models with deep learning, tailored to specific industries, holds the most promise for accurate and actionable customer behavior prediction.

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