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The Role of Artificial Intelligence in Revolutionizing Personalization and Customer Engagement

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Abstract

Artificial Intelligence (AI) is changing the world of online shopping by creating tailored experiences for customers and improving customer interactions. In this paper, the study shows how AI methods like Natural Language Processing (NLP) and machine learning are helping to study customers' feedback and scores to create customized recommendation systems. The fusion of sentiment analysis and collaborative filtering-based recommender systems results in higher customer satisfaction rates and better customer experiences, and helps businesses build customer loyalty by employing personalised touchpoints. It enhances organisations' operational activities and helps them remain competitive for a long time. A dataset of 363K product reviews is used for sentiment analysis and to build a recommendation system. The research shows connections between how customers feel about a product, their ratings, and their buying habits, offering ideas for using AI to enhance personalised business strategies.

Keywords: *Customer Engagement, Sentiment Analysis, Personalisation, Recommender Systems, Machine Learning, Natural Language Processing, Product Reviews, Customer Satisfaction.*

1. Introduction

In nations around the world today, the use of AI and machine learning is reshaping how decisions are made in e-commerce marketing by refining pricing strategies and making marketing campaigns more effective. For example, research has shown that companies are heavily relying on AI to tailor marketing efforts to customers and automate tasks, leading to higher customer satisfaction and increased sales. Now, companies place great emphasis on using AI and ensuring data security standards, as these factors play a role in building trust with consumers [1]. Most companies worldwide are adopting AI to analyse consumer behaviour, enabling them to quickly adapt to market trends and refine their marketing strategies. Various research efforts are increasingly embracing AI to automate marketing tasks and elevate customized customer interactions. Additionally, corporations are concentrating their efforts towards AI-powered solutions to streamline logistics processes and reduce expenses. Businesses can gain insights from these experiences, such as adopting proven technologies and accessing cutting-edge AI and machine learning advancements, by studying successful case examples from around the world. The primary goal of the study is to create a structure that integrates AI and ML into e-commerce marketing practices by examining their effects on consumer behaviour and marketing effectiveness, and by refining sales tactics efficiently. Moreover, the research aims to explore the use of AI and ML technologies to enrich customer interactions and marketing operations, and to facilitate data-driven decision-making within the realm of e-commerce [2].

The aim is to offer tips and ideas for online retail companies to leverage AI and machine learning effectively. These tips are designed to improve how businesses operate by cutting costs and enhancing customer satisfaction and loyalty. Here, the goal is to help companies enhance their advertising efforts and predict market shifts. It would help in staying ahead of the competition in today's fast-changing digital world.

2. LITERATURE REVIEW

Customer service is a very important aspect of the retail business, as it directly affects customers' loyalty and satisfaction. The change in customer selection and customisation also poses a challenge for retailers. Thus, they need to develop ways to enhance their customer service [3]. AI has the potential to enhance customer service via real-time support and personalised recommendations. Thus, it is crucial to incorporate AI into customer service to meet rising consumer expectations and stay competitive.

Data analytics has forced the retail industry into revolution by providing valuable insights into customer behaviour and market trends. Leveraging data analytics, retailers can make optimized marketing strategies, data-driven decisions and enhance overall shopping experience [5]. The integration of cloud computing solutions enables real-time decision-making and sophisticated predictions, which are crucial for staying competitive and evolving the retail landscape [4, 6].

Personalisation is one of the strategies of modern marketing and has been enhanced by AI. The traditional personalization systems were constrained by the amount of data that was collected about customers. But it is possible to provide real-time, accurate personalisation with the help of AI, leveraging ML algorithms and customer insights. Recommender systems (RS) are systems that provide personalised product recommendations to customers based on their buying preferences. RS models, used by firms such as Amazon and Netflix have been shown to enhance customer satisfaction and retention.

The incorporation of AI technologies such as ML, NLP, and computer vision has improved the customer experience by enabling more convenient, tailored interactions. Figure 1 shows the workflow of an AI-based recommendation system. Sentiment analysis of customers' interactions with robots identifies customer requirements and produces valuable insights, while recommender systems enhance the customer experience and satisfaction. The analysis of the literature shows that the companies that use AI to analyse sentiment and feedback of customers see a boost in customer loyalty and trust [7].

Figure 1: Work flow diagram of AI-based recommendation system

The current research indicates that the integration of AI and personalisation is one of the key pillars defining the future of customer loyalty in trade and retail. By analysing customer behaviour, AI algorithms can display personalised ads, product recommendations, and content to engage customers more effectively [8]. This approach increases customer interaction and satisfaction as well. Table 1 summarises some of the ideas presented by the authors, along with their limitations.

Table 1: Summary of Various AI-based Personalization

Author(s)	Year	Idea	Problem	Fix
N. Darraz, I. Karabila, A. E.Ansari, N. Alami, and M. E. Mallahi,	2025	Integrated sentiment analysis with BERT for hybrid recommendation systems	Limited to static sentiment extraction	Use real-time sentiment updates
M. Barari, S. Quach, and P. Thaichon	2022	AI-powered products in marketing	Lacks personalization depth	Integrate recommender systems with sentiment analysis
V. Kumar, B. Rajan, S.Gupta, and I.P.Dalla,	2019	Machine learning for e-commerce performance	Focuses on sales, not engagement	Include customer sentiment for engagement insights
T. Nguyen and K. Ho	2021	NLP for targeted marketing	Limited feedback loop	Add dynamic recommendation updates

3. PROPOSED SYSTEM

The proposed system has two main components, a sentiment analysis model and a recommendation system. E-commerce personalization and customer interaction are combined in this framework, to enhance the customers' experience and make their purchasing journey more engaging.

3.1 Sentiment Analysis

Sentiment analysis refers to the process that analyses written or spoken language and establishment of the emotional tone behind a series of words, which is used in customer reviews or feedback. It's a type of text analysis that uses Natural Language Processing (NLP) same as VADER.

Valence Aware Dictionary and sEntiment Reasoner (VADER) is a more effective tool that is designed to assist marketers in analysing sentiments and social media activity of users. It evaluates the text in question, and the author's attitude towards the object of study is scored from -1 (most negative) to +1 (most positive) [12].

Customer reviews are collected from the e-commerce platform and converted into expressing appreciation for the purchased items. Using VADER, each review is presented with a sentiment score. These scores are then subdivided into three categories:

***Positive**:* It shows that customers are happy with the service provided.

***Neutral**:* It discusses customers' feelings, neither pleasant nor disappointing.

Negative: Shows a customer is not pleased with the service offered.

Sentiment information plays a role, in aiding the system to grasp customer perceptions on products effectively. By analysing this data, businesses can uncover insights, like trending product attributes and frequent grievances, empowering them to improve their offerings.

3.2 Recommender System:

A Recommender System proposes products to the user based on his preferences, behavior or history of interactions with the system. In this system, the recommendation model is built using a combination of collaborative filtering methods [9, 13].

The recommender systems can be classified into various types, including collaborative filtering, which is a recommendation where users are asked to rate several items, and the system uses all the ratings supplied by the other users to try and predict the likes of the specific user. It is based on the logic "people who liked this item also liked that item."

User-based recommendations are preference-based, using other users who have shown interest in the items.

Item-Based is a recommendation method that uses artificial intelligence to suggest items similar to those they have valued and helped promote [13].

Customer activities, such as rating a product or an item, along with purchase history and items viewed, are recorded in a dataset. The system employs a collaborative filtering approach that generates a matrix of user-item interactions, for instance, ratings. For a new user, it looks for matches with other users or products and makes an assumption about how much the user would like an item that they have not already rated. From the given ratings, the system can recommend products that are most likely to be desirable to the user. The recommendations are further optimized based on the increasing data set and the user's feedback to make the model more intelligent.

4. METHODOLOGY

The data set used in this research is about 363,261 entries and it has the following key attributes:

- Product Name: Name of the different products offered.
- Price: Cost of the product.
- Rate: Customer ratings (on a scale of 1 to 5).
- Review: This involves the average short text review done upon a product.
- Summary: This is an in-depth report or appraisal of the product.

Sentiment Analysis Model built using natural language processing techniques to elaborate on the reviewer/summary texts. The polarity of the reviews (positive, neutral, or negative) was classified using the VADER sentiment analysis tool, enabling us to build a sentiment analysis model [17]. This enabled us to classify customer sentiment based on the review text. After the Sentiment Analysis Model, we created a collaborative filtering recommendation model based on matrix factorisation. The model recommends products based on customers' common preferences, predicting and recommending products based on customer ratings. For the sentiment analysis, polarity scores were classified into three categories as shown in Figure 2.

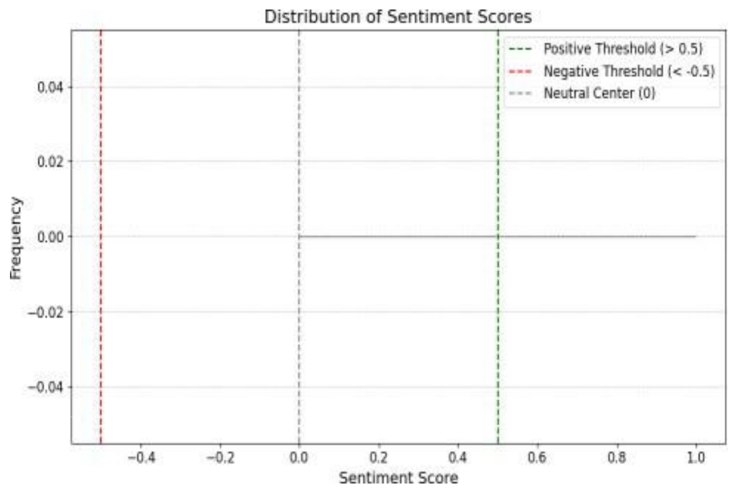

Figure 2: Distribution of Sentiment Scores

4. RESULTS AND DISCUSSION

Here we outline the results of sentiment analysis and the recommender system, and how they enhanced customer interaction and customization in e-commerce.
The sentiment analysis of 363,261 customer reviews in order to determine the polarity of the reviews used the VADER sentiment scoring method to categorize the reviews into three groups: positive, neutral and negative. Based on the sentiment analysis, the following distribution of sentiment categories was made:

- Positive Sentiments: 276,286 reviews (76.08%)
- Neutral Sentiments: 51,596 reviews (14.21%)
- Negative Sentiments: 35,379 reviews (9.71%)

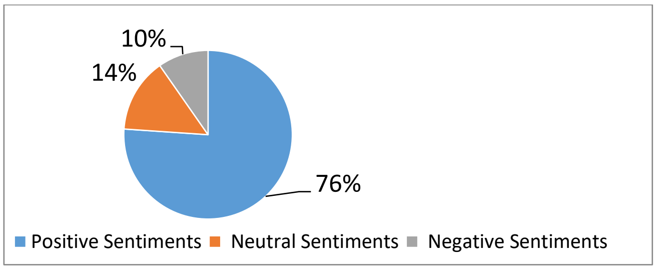

Figure 3: Illustration of Sentiments

Management should be pleased with the analysis's outcome, as it shows a clear dominance of positive sentiment, which should indicate good customer satisfaction for most products [14]. The high ratio of positive feedback indicates that the analysed products meet most customers' needs. Figure 3 illustrates the sentiment ratios and shows that positive opinions exceed neutral and negative opinions. This imbalance is very useful for companies, as it allows them to pinpoint the most successful items whilst also using sentiment analysis to manage issues highlighted by negative or neutral feedback.

The first collaborative filtering approach highlights the top 5 products with the highest average ratings, as recommended by users in the dataset. As seen in Figure 4, all five products averaged 4.0 or higher, with a near 5.0, indicating a high level of customer satisfaction. The products are included:

5. BAJAJ FX7600.
6. Sasino 1.8 L.
7. ZunVolt Power MG5.
8. Lopez's Microfiber Floor.
9. HYGEX Magic Copy.

The results show that the recommender system is in line with customers' preferences as it recommends products that are rated highly and well received by the customers. This also shows that the collaborative filtering method is effective at identifying the products most suitable for customers.

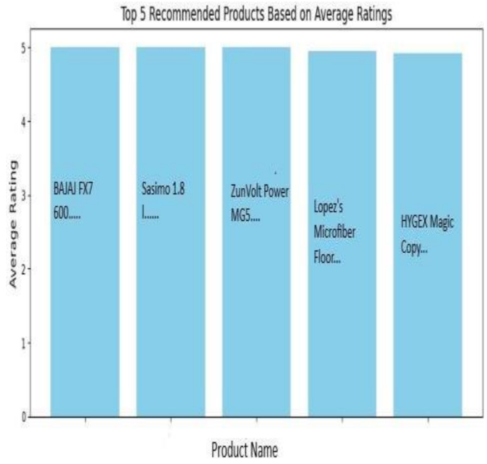

Figure 4: Average Ratings of Products

4.1 Integration of Sentiment Analysis and Recommender System

The sentiment analysis is integrated with the recommendation engine to improve the level of personalisation for the customers. Products with mainly positive reviews were recommended more often, leading to happier customers. On the other hand, the items that had a large percentage of negative reviews were demoted or not recommended at all with the aim of enhancing the accuracy of the recommendations made. This helps enhance customer participation by presenting only the best-rated products to customers, thereby building confidence and loyalty.

4.2 Evaluation Metrics

Evaluation metrics are crucial for effectively assessing the system's performance [18]. For this research, the following metrics are applied:

- Accuracy

The sentiment classification was nearly 80%, indicating that the number of correctly predicted positive, negative, and neutral sentiments was quite high.

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+TN+FP}$$

- Precision and Recall

These metrics established a solid classification performance of the model where it is accurately able to identify the sentiment categories while reducing the probability of making false predictions.

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

- F1-Score

The F1-score showed a balanced compromise between the precision and recall, and it is crucial for the problem of dealing with the imbalanced sentiment classes.

- Root Mean Square Error (RMSE)

The RMSE is calculated to be low, indicating then the predicted ratings are quite close to the real user ratings. This strengthens the notion that the collaborative filtering algorithm is quite effective in identifying customer preferences as well as predicting their preferences.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}$$

where n = number of data points, y_i^= predicted value and y_i = actual/observed value.

Table 2 presents results supporting the hypothesis that applying AI techniques, including sentiment analysis and collaborative filtering, can greatly improve personalisation in e-commerce. The proposed algorithm has identified products that meet the customer's requirements, thereby enhancing both the website's usability and conversion rate. This means that by paying attention to the products that receive positive sentiment and are highly rated, companies can fine-tune their marketing plans as well as their inventory control and thus boost their sales and customer satisfaction. This can be attributed to the fact that positive sentiment is a strong indicator of customer satisfaction, which, in turn, influences purchase behaviour and product recommendations.

Table 2: Result matrix

Accuracy	0.825
Precision	0.871
RSME	0,932
F1	0.844

5 CONCLUSION

This study explains how artificial intelligence (AI) can transform the fields of personalisation and customer engagement in e-commerce by combining sentiment analysis with collaborative filtering-based recommender systems. Sentiment analysis identified customers' perceptions, with 76.08% of positive reviews focused on overall consumer satisfaction. Such a recommender system used the data to recommend products with the most positive reviews first and downplayed those that were not well rated. The fusion of the two should result in higher customer satisfaction rates, better customer experiences, and help businesses build customer loyalty by employing personalised touchpoints. The proposed algorithm achieves 82.5% accuracy using collaborative filtering with sentiment analysis. The application of Artificial Intelligence puts organisations in a position to optimise decision-making, enhance operational activities, and remain competitive in an ever-changing digital environment. Further research can focus on using real-time consumer feedback and applying it to more advanced Artificial Intelligence models for refinement.

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