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Sentiment Our Recommended System For E-Commerce Platform Using Large Language Model

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Abstract
Background: *With the rapid expansion of e-commerce platforms, personalized product recommendation systems have become essential for enhancing user satisfaction and business performance. Traditional systems primarily rely on user-item interactions, often neglecting the emotional context present in customer reviews.*
Problem: *Conventional recommendation models struggle to capture sentiment-driven user preferences, leading to less relevant or generic suggestions. Moreover, the lack of optimization and contextual understanding limits the adaptability and accuracy of these systems.*
Methods: *To address this gap, we propose a hybrid sentiment-aware recommendation framework combining Bidirectional Encoder Representations from Transformers (BERT) for deep sentiment feature extraction, the Marine Predators Algorithm (MPA) for optimization, and a Decision Tree (DT) and clustering for interpretable classification. The model integrates sentiment scores into the recommendation pipeline to refine user profiling and improve suggestion relevance.*
Results: *The proposed MPA_BERT+DT system was evaluated on datasets from three real-world platforms like Chase Technologies, SJ Enterprise, and Order Your Choice. It outperformed existing algorithms such as Naive Bayes, SVM, Random Forest, and baseline BERT, achieving an accuracy of 94.0%, with statistically significant improvements in precision, recall, and F1-score.*
Conclusion: *The MPA_BERT+DT model delivers a scalable and effective recommendation approach that combines sentiment analysis, optimization, and explainable classification. It enhances personalization, increases user trust, and demonstrates clear potential for real-world deployment in sentiment-rich e-commerce environments.*
Keywords: *Sentiment Analysis; Recommender System; BERT Model; Marine Predators Algorithm (MPA); Decision Tree Classification; E-commerce Personalization*

1. INTRODUCTION

A recommendation system in an e-commerce platform is a powerful tool designed to personalize the shopping experience by suggesting products that align with the user's preferences, behavior, and purchase history. These systems analyze vast amounts of user data, such as browsing patterns, previous purchases, ratings, and items added to carts or wishlists. Based on this data, recommendation algorithms generate tailored suggestions that enhance customer engagement and drive sales. The most common types of recommendation systems used in e-commerce include collaborative filtering, which relies on user-item interactions, and content-based filtering, which focuses on the features of products a user has shown interest in. Advanced models combine both approaches using hybrid techniques and deep learning for better contextual understanding. Additionally, systems may use sentiment analysis of product reviews to refine suggestions by evaluating customer feedback. Overall, recommendation systems play a crucial role in increasing conversion rates, boosting user satisfaction, and improving overall business performance in the e-commerce domain.

Sentiment analysis plays a pivotal role in enhancing the intelligence of recommendation systems by providing deeper insights into user preferences beyond mere clicks and ratings. While traditional recommender systems focus on quantitative interactions such as product views or purchase history, sentiment analysis adds a qualitative dimension by evaluating the emotional tone of user-generated content such as reviews, comments, and feedback. This allows the system to understand why a user liked or disliked a product, offering a more accurate and human-centric perspective. For instance, a user might rate a product positively but express dissatisfaction in the review text—something only sentiment analysis can detect. By extracting and interpreting sentiments, the system can better personalize recommendations, filter out negatively reviewed items, and even detect emerging trends or concerns. Eventually, integrating sentiment analysis helps in refining recommendation accuracy, increasing user satisfaction, and building trust in the e-commerce platform, making it a vital component of modern intelligent recommender systems.

Sentiment analysis employs a wide range of algorithms to classify text data based on the emotional tone expressed. These algorithms are generally divided into three categories: machine learning-based, lexicon-based, and deep learning-based approaches. In traditional machine learning, commonly used algorithms include Naive Bayes, Support Vector Machine (SVM), Logistic Regression, and Decision Trees, which rely on labeled datasets and features like term frequency and inverse document frequency (TF-IDF). Lexicon-based methods, such as VADER (Valence Aware Dictionary and sentiment Reasoner) and SentiWordNet, use predefined dictionaries of sentiment-labeled words to analyze text without needing training data. With the rise of deep learning, advanced models like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers) have become popular due to their ability to capture context, semantics, and word dependencies more effectively. Hybrid models that combine lexicon methods with learning-based techniques are also used to improve accuracy and adaptability across diverse datasets.

Despite their widespread adoption, existing recommendation methods in e-commerce platforms face several significant drawbacks that limit their effectiveness. Traditional approaches like collaborative filtering often suffer from the cold start problem, where the system struggles to generate accurate recommendations for new users or items due to a lack of historical data. Similarly, content-based filtering tends to offer limited diversity, recommending items that are too similar to what the user has already seen, thereby reducing novelty and exploration. Another major challenge is data sparsity, where the number of user-item interactions is insufficient to build robust predictive models. Moreover, most recommendation systems rely heavily on explicit feedback like ratings, overlooking the richer insights found in implicit feedback such as click behavior or review sentiments. Existing models also often lack the ability to understand contextual information like time, location, or user mood, which can influence preferences. Furthermore, they may fail to detect sentiment polarity in user reviews, potentially recommending products that have been negatively received. These limitations highlight the need for more intelligent, context-aware, and sentiment-driven recommendation systems.

The integration of Large Language Models (LLMs), such as BERT, GPT, and their derivatives, has revolutionized sentiment-based recommendation systems by enabling more accurate and context-aware understanding of user preferences. These models are pre-trained on vast corpora of text data and can comprehend the nuances of human language, including sarcasm, slang, and contextual dependencies, which traditional models often fail to capture. In sentiment analysis, LLMs excel at extracting deep semantic features from user reviews, comments, and social media posts, allowing the recommendation engine to better gauge user satisfaction or dissatisfaction. This enriched sentiment understanding can then be directly incorporated into the recommendation pipeline, enabling the system to prioritize products that not only match a user's interests but also align with positively received sentiments. Furthermore, LLMs support zero-shot and few-shot learning, allowing them to adapt quickly to new domains with minimal labeled data. By utilizing these capabilities, sentiment-based recommendation systems become more dynamic, personalized, and context-aware, ultimately leading to improved user experience and higher engagement on e-commerce platforms.

Problem statement

In the current landscape of e-commerce, recommendation systems play a crucial role in guiding users toward relevant products. However, these systems are often constrained by multiple unresolved issues that limit their personalization capabilities. A key concern is their dependence on large volumes of user interaction data, making them less effective for new users or items a challenge known as the cold start problem. Furthermore, in platforms with an extensive catalog, the interaction data becomes increasingly sparse, reducing the precision of item suggestions. Many existing models also rely heavily on structured data like ratings or past purchases, while largely ignoring unstructured data such as product reviews and customer feedback. This results in a shallow understanding of user intent. Additionally, most systems lack the ability to capture contextual nuances such as evolving user preferences, seasonal demand shifts, or sentiment trends over time. The absence of sentiment-driven insight often leads to product recommendations that may be statistically relevant but emotionally misaligned with the user's experience.

These shortcomings underscore the need for more adaptive systems that incorporate user sentiment, context-awareness, and behavior analysis to enhance recommendation quality in real time.

Research gap

While traditional recommendation systems have significantly improved product discovery and user personalization in e-commerce platforms, they largely rely on numerical feedback like ratings or past interactions. This approach fails to capture the underlying emotions and opinions expressed by users in reviews or comments. Although sentiment analysis has been introduced in some models to address this, existing systems often use basic lexicon-based methods or shallow classifiers, which struggle to understand the context, sarcasm, or nuanced language. Moreover, the integration of sentiment scores into the recommendation pipeline is often limited to static weighting schemes that do not adapt to user behavior over time. Recent advancements in LLMs such as BERT and GPT offer the potential to deeply analyze review content and extract sentiment in a more context-aware and dynamic manner. However, a notable gap remains in how effectively these LLM-generated sentiment scores are fused with recommendation algorithms for real-time personalization. There is a lack of unified frameworks that seamlessly embed these sentiment embeddings or scores into user-item matrices or ranking models, especially in a scalable and interpretable way. Addressing this gap can lead to more emotionally intelligent and user-aligned recommendation systems.

Contributions

(i) **To integrate deep contextual sentiment understanding** into recommendation systems by utilizing BERT embeddings for extracting nuanced emotional cues from user reviews.

(ii) **To optimize user preference matching** using MPA, enhancing the alignment between sentiment features and recommendation accuracy.

(iii) **To improve interpretability and decision transparency** by employing DT classifier for final recommendation generation within a hybrid DL optimization framework.

(iv) **To validate the model across diverse real-world datasets** from multiple e-commerce platforms, demonstrating consistent improvements in accuracy, user satisfaction, and business productivity.

The structure of this paper is as follows: **Section 2** reviews related work and identifies research gaps. **Section 3** explains the proposed methodology integrating sentiment analysis with optimization. **Section 4** presents experimental results and discussion. **Section 5** concludes the study and outlines future scope.

2. LITERATURE SURVEY

In the contemporary e-commerce environment, understanding customer sentiment has become essential for businesses striving to enhance competitiveness and tailor offerings to consumer needs. One such effort was undertaken by Naidu and Ramesh **[1]**, who explored the sentiment expressed in customer reviews related to popular Indian fashion brands such as Myntra, Ajio, and Tata Cliq. They applied a transformer-based language model (BERT) to analyze unstructured textual data from reviews. The study addressed the problem of unrecognized customer emotions in fashion e-commerce and demonstrated how deep contextual embeddings could be harnessed to extract valuable insights for brand improvement. The problem of inaccurate sentiment and emotion classification due to data inconsistencies in user-generated content was addressed in a study focusing on Bangla e-commerce data **[2]**. This work recognized that noise and discrepancies in the data significantly hinder the performance of sentiment analysis models. The authors implemented a two-phase framework where inconsistencies were first identified and rectified, followed by the application of a BERT model for emotion and sentiment analysis. This process helped achieve more consistent and insightful outcomes, highlighting the importance of robust data preprocessing in ensuring the reliability of sentiment interpretation. Another critical issue in the digital economy is the need to understand whether customers would recommend products based on their reviews. A study **[3]** aimed to uncover such behavior patterns using natural language processing methods. The authors noted that most prior sentiment research primarily focused on developed economies, leaving a gap in understanding emerging e-commerce markets. Through textual analysis of customer reviews, the study sought to predict post-purchase satisfaction and recommendation tendencies, providing a deeper understanding of consumer decision-making. To further enhance sentiment understanding at a granular level, researchers explored aspect-based sentiment analysis (ABSA) using transformer models **[4]**. This study identified a gap in capturing sentiment polarity toward specific features within a product or service. By using pretrained models such as BERT, the authors were able to discern aspect-level opinions in reviews. The method offered a scalable and detailed approach, contributing to the development of intelligent systems capable of fine-grained feedback analysis. Understanding emotional expression in user reviews also gained attention in work focusing on extracting contextual sentiment cues using the XLNet model [5]. This research responded to the need for identifying subtle emotional indicators that traditional models often miss. The system was designed to interpret intricate sentiment patterns within customer feedback, thereby aiding industries like e-commerce, healthcare, and entertainment in enhancing customer satisfaction and service quality.

Emotion classification using classical machine learning approaches was studied in the context of the Tokopedia platform [6]. The authors tackled the challenge of data imbalance and employed various variants of the Naïve Bayes algorithm to classify emotional tone in reviews. They demonstrated how different sampling techniques could impact classification outcomes, thus emphasizing the importance of model selection and data handling in sentiment-based classification tasks. The integration of sentiment analysis into recommendation systems presents another innovative direction, as explored in a study that proposed a sentiment-aware recommendation framework [7]. The main issue addressed was the lack of personalization in traditional recommender systems. By analyzing the underlying emotions in user reviews and interfacing with users through a conversational chatbot built with OpenAI tools, the system improved both user interaction and recommendation relevance. Another important dimension in modern e-commerce is sustainability. A study [8] explored how customer emotion detection could support sustainable consumption behavior. The authors recognized the challenge of aligning commercial goals with environmental consciousness and proposed a machine learning framework that detects user emotions in real time. The insights derived were used to customize digital experiences, reduce the environmental footprint of consumption, and develop ethical marketing practices. The problem of capturing nuanced feedback from product reviews was addressed through a hybrid model combining unsupervised and supervised techniques [9]. The study presented a three-step process involving aspect term extraction, opinion term extraction, and sentiment scoring. An unsupervised rule-based model was used to extract meaningful phrases, and a BERT-based classifier assigned sentiment values. This comprehensive approach helped vendors interpret customer opinions more effectively, facilitating targeted product improvements. In another work, the effectiveness of classical machine learning classifiers—Support Vector Machine and Random Forest—was evaluated using Flipkart product reviews [10]. The study identified the lack of comparative research in this domain and aimed to assess the strengths and limitations of each approach. The findings contributed insights into optimal classifier selection for sentiment categorization in highly competitive e-commerce environments. Advanced neural network architectures were also explored to overcome the limitations of traditional sentiment models. One such study [11] employed a CNN-based LSTM model to analyze Amazon product reviews. This work addressed the limitations of previous models in capturing long-term dependencies in text and demonstrated the potential of hybrid deep learning techniques in achieving robust sentiment classification. Sentiment analysis models have also been evaluated for their ability to interpret large-scale data from diverse sources such as Twitter, Instagram, and e-commerce sites. A comprehensive study [12] constructed a full pipeline for emotion prediction and evaluated several machine learning models. The research provided clarity on model performance across different platforms and established practical methodologies for real-world sentiment analysis applications.

A novel sentiment classification approach using ensemble learning was introduced to overcome the limitations of binary classification in capturing the diversity of emotional expressions [13]. This method applied to Flipkart reviews successfully modeled complex emotions, thereby enhancing the interpretability and usefulness of sentiment data in business analytics. In addressing the challenges of long-distance dependencies in textual data, a hybrid approach was proposed that combined an improved Transformer model with a Conditional Random Field (CRF) classifier [14]. This model was further augmented with LSTM components to improve feature capture. The research demonstrated how architectural enhancements could lead to better understanding of sentiments embedded in long-form texts. Finally, a study focusing on the emerging Customer-to-Manufacturer (C2M) model developed a service quality evaluation framework using topic modeling and deep learning [15]. The research responded to the need for identifying areas of customer dissatisfaction in personalized service environments. By combining LDA for theme extraction with a BiLSTM-based sentiment model, the study provided actionable insights into the emotional drivers of negative feedback, thereby assisting businesses in optimizing service delivery.

Inferences from literature survey

The literature survey reveals that transformer-based models such as BERT and XLNet effectively capture nuanced sentiments and emotions in e-commerce reviews. Preprocessing steps, particularly discrepancy removal, play a crucial role in enhancing classification accuracy. ABSA enables deeper insights into customer opinions on specific product features, while hybrid deep learning models like CNN-LSTM and Transformer-CRF outperform traditional classifiers in handling complex sentiment patterns. Classical algorithms like Naïve Bayes, SVM, and Random Forest remain useful, especially when optimized through resampling. Emotion detection contributes significantly to improving recommendation systems, customer satisfaction, and sustainable e-commerce practices. Integrating topic modeling with sentiment analysis helps identify the underlying causes of negative feedback, supporting targeted improvements. Additionally, ensemble and transfer learning approaches offer robust and scalable sentiment classification solutions. Finally, regional studies highlight the growing importance of culturally contextual sentiment analysis in emerging e-commerce markets.

3. METHODOLOGY

As illustrated in **Figure 1**, the proposed sentiment-aware recommendation system integrates user-generated reviews, sentiment scoring, and a feedback-driven optimization loop to enhance product recommendations and improve e-commerce performance.

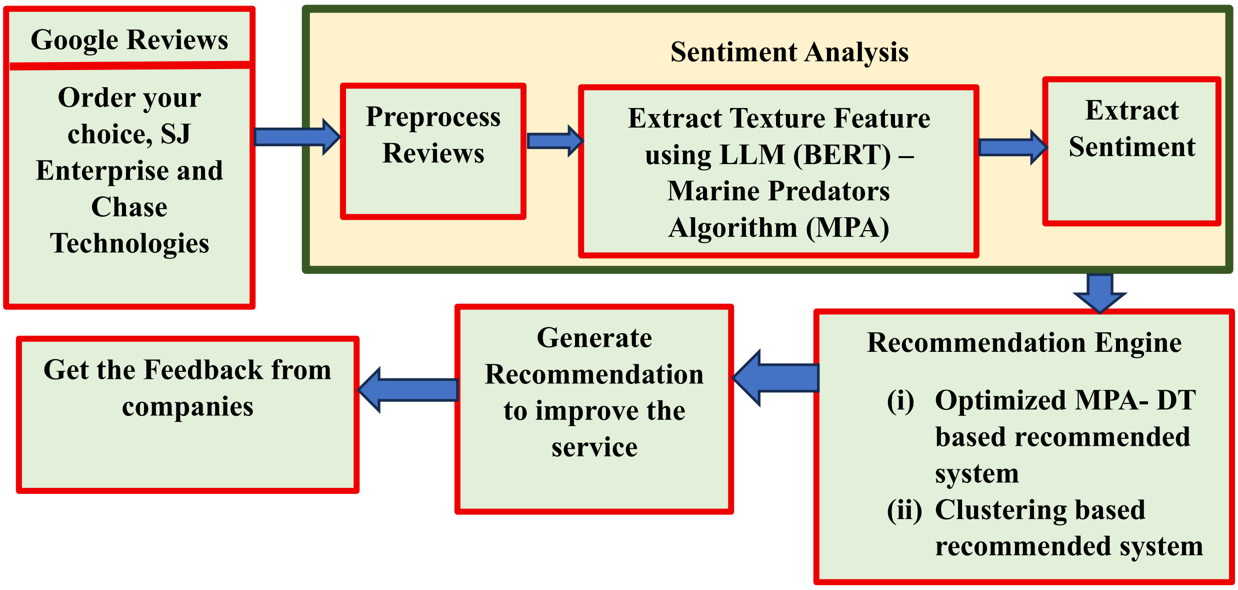

Fig 1 Block diagram of proposed algorithm

The process initiates with the input of customer reviews, gathered from platforms such as Google Reviews for businesses like "Order Your Choice," "SJ Enterprise," and "Chase Technologies." These raw reviews are subjected to a comprehensive preprocessing pipeline that removes irrelevant components including stop words, emojis, numbers, and special characters to clean the textual data. The cleaned text is then tokenized and passed through an embedding encoder, which transforms the words into numerical vector representations suitable for further analysis.

Following embedding, a sentiment analysis module powered by a large language model extracts sentiment scores from the reviews. These scores are then mapped to specific user-product pairs, enabling the construction of a sentiment matrix that captures user attitudes toward different products. This matrix serves as the input to train the recommendation model, which employs the Marine Predators Algorithm (MPA) for optimizing weight assignments and feature selection. The optimized features are subsequently processed by a Decision Tree classifier, which generates personalized product recommendations based on both behavioral and emotional feedback.

A unique feature of the system, as depicted in the flow structure (**Figure 2**), is the closed-loop feedback mechanism. Post-recommendation, company feedback is collected to evaluate whether the recommendations have contributed to an increase in product sales. A decision node assesses the effectiveness of the system: if sales performance improves, the process is deemed successful; otherwise, the loop continues, allowing the system to dynamically retrain and adapt using updated sentiment and behavioral data. This cyclical process ensures continual refinement of the recommendation engine, making it more context-aware, sentiment-driven, and business-responsive over time.

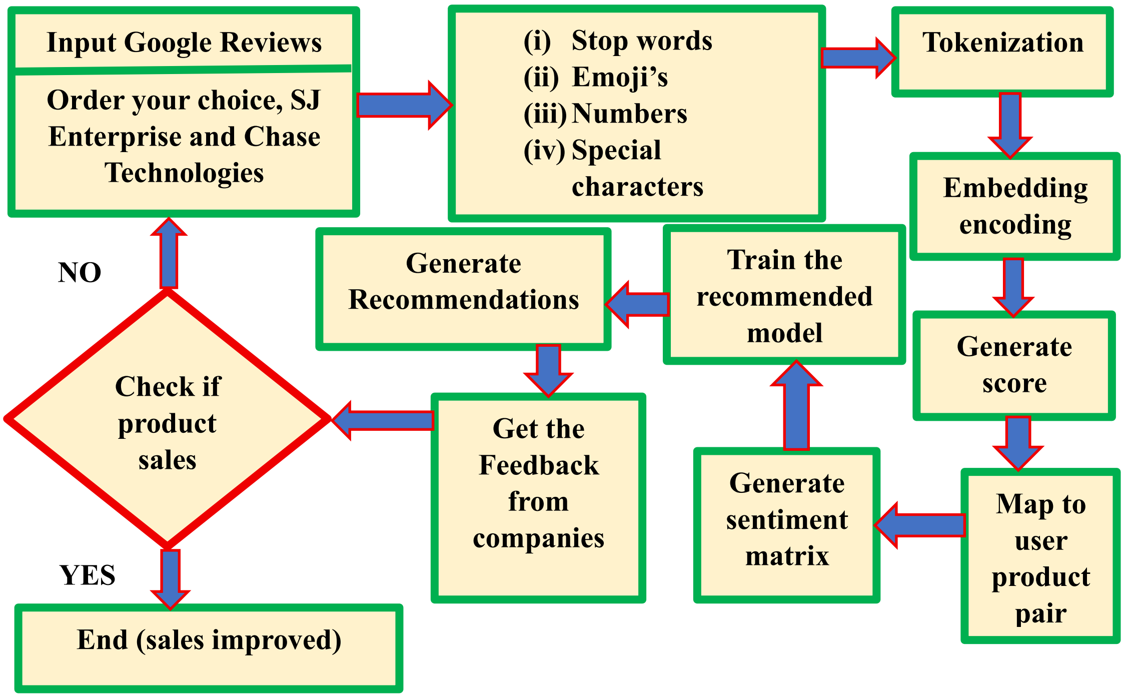

Fig 2 Flow chart

3.1. Bidirectional Encoder Representations from Transformers (BERT)

In e-commerce recommendation systems, BERT model plays a vital role in understanding the contextual meaning of user reviews and product descriptions. Unlike traditional models that rely on keyword frequency or shallow sentiment analysis, BERT captures the deeper semantic relationships within sentences by processing text bidirectionally. This allows the recommendation engine to extract more accurate sentiment cues, intent, and preferences from user feedback, enabling personalized and sentiment-aware product suggestions. Its ability to understand subtle nuances in language greatly enhances the relevance and quality of recommendations, leading to improved user satisfaction and engagement in online platforms.

3.2. Marine Predators Algorithm (MPA)

The Marine Predators Algorithm (MPA) is a modern nature-inspired metaheuristic that emulates the intelligent hunting behavior of marine predators in aquatic ecosystems. Unlike traditional optimization techniques, MPA dynamically alters its search strategy based on the interaction ratio between predator and prey speeds drawing directly from natural oceanic food chain dynamics. The algorithm consists of three phases that simulate exploration, transition, and exploitation behaviors. These phases are governed by how predators respond to the movement speed of prey, allowing the algorithm to switch from wide-ranging global exploration to concentrated local refinement. Early in the optimization process, MPA encourages widespread search across the solution space to discover diverse potential solutions. As iterations progress, it gradually narrows its focus, mimicking how real predators intensify their pursuit as prey becomes slower or more predictable. The strength of MPA lies in its ability to maintain a balance between diversity (to avoid local optima) and convergence (to find high-quality solutions), making it highly suitable for complex, multi-dimensional problems such as those found in sentiment-aware recommendation systems. Its integration of Brownian motion and Lévy flight strategies enables robust randomization patterns, adding further depth to its search mechanism and mimicking real-world unpredictability in predator movement.

Phase 1 – Global Exploration (Prey is faster) in Equation (1):

$$\boldsymbol{X_i^{t+1} = Elite + \left|F.Elite - F.X_i^t\right|} \quad (1)$$

Phase 2 – Transition Phase (Equal speeds) in Equation (2):

$$\boldsymbol{X_i^{t+1} = X_i^t + F.(Elite - X_i^t} \quad (2)$$

Phase 3 – Exploitation (Prey is slower) in Equation (3):

$$\boldsymbol{X_i^{t+1} = Elite + F.(Elite - X_i^t)} \quad (3)$$

Where, F is generated using Brownian motion for exploration and Lévy distribution for exploitation. The algorithm uses random walks for diversification and elite-based learning for intensification.

In sentiment-aware recommendation systems, traditional optimizers often fall short in adapting to the dynamic nature of user preferences and review sentiments. MPA is particularly well-suited for this problem space due to its multi-phase adaptive search strategy, which mimics the changing behaviors in user-product interaction over time. While user sentiment data is inherently noisy, emotional, and variable, MPA's use of stochastic movements such as Brownian motion and Lévy flights helps in escaping local optima and discovering more accurate mappings between user sentiment and product features. Moreover, in hybrid recommendation systems where sentiment embeddings (e.g., from BERT) are fused with collaborative filtering or classification models, MPA serves as a reliable method for hyperparameter tuning, threshold adjustment, and feature weighting. Its elite-driven memory and global best convergence behavior ensure that the recommendation outcomes are not only statistically optimized but also emotionally aligned with user feedback. The incorporation of MPA enhances both precision and personalization, which are crucial for user satisfaction in modern e-commerce platforms. Its compatibility with deep feature representations and feedback loops makes it an ideal optimization backbone for your proposed architecture.

Marine Predators Algorithm (MPA)
Input: Objective function f(x), population size N, dimension D, max iterations T *Output: Best solution Elite* *1. Initialize population X randomly within bounds* *2. Evaluate fitness of each agent; set Elite = best agent* *3. For t = 1 to T:*   *P = t / T ← normalized time*   *For each agent i in X:*   *If P < 1/3:*   *// Phase 1: Global exploration*   *X[i] = Elite + |randn() * Elite − randn() * X[i]|*   *Else if P < 2/3:*   *// Phase 2: Transition*   *X[i] = X[i] + randn() * (Elite − X[i])*   *Else:*   *// Phase 3: Exploitation using Lévy flight*   *X[i] = Elite + Levy() * (Elite − X[i])*   *Enforce boundary limits*   *Update Elite if better solution is found* *4. Return Elite and its fitness*

3.3. Decision Tree–Based Recommendation System

A Decision Tree–based recommendation system is a supervised learning model that classifies user preferences and recommends items by learning decision rules from labeled data. It operates by recursively splitting the dataset based on feature values (e.g., user demographics, sentiment scores, item categories) to predict the most relevant item for a given user. Decision trees are interpretable and work well when features such as user sentiment polarity, purchase history, or review scores are known. In a sentiment-integrated context, the decision tree receives inputs like Sentiment score from reviews, Product category, User behavior features and Product popularity index. Based on these features, it builds a tree structure where each internal node represents a decision rule (e.g., "sentiment > 0.7"), and each leaf node corresponds to a product recommendation.

Information Gain (used in entropy-based trees) in Equation (4):

$$\boldsymbol{IG(D, A) = Entropy(D) - \sum_{v \in Values(A)} \frac{|D_v|}{|D|} Entropy(D_v)} \quad (4)$$

3.4. Clustering-Based Recommendation System

A Clustering-based recommendation system is an unsupervised approach that groups similar users or products into clusters using similarity measures. Recommendations are then made by suggesting popular items within the user's cluster. For example, K-Means is commonly used to identify user segments based on features like browsing behavior, sentiment vectors, or demographic data. In a sentiment-enhanced system, clustering is applied on vectors such as User review sentiment embeddings (from BERT or TF-IDF), Purchase frequency and Browsing session duration. Once clustering is complete, recommendations are based on top-rated or most purchased items within the same cluster.

K-Means Clustering Objective in Equation (5):

$$\boldsymbol{min\ C} \sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2 \qquad (5)$$

Where, C_i = cluster i, μ_i = centroid of cluster i.

Decision Tree Classifier	cluster import KMeans
# Sample input: Features from reviews and metadata *X = [[0.8, 1], [0.2, 0], [0.7, 1], [0.1, 0]] # [sentiment_score, product_popularity]* *y = ['Recommend', 'Don't Recommend', 'Recommend', 'Don't Recommend'] # Labels* *# Train decision tree model* *model = DecisionTreeClassifier(criterion='gini', max_depth=3)* *model.fit(X, y)* *# Predict on a new review* *new_input = [[0.75, 1]]* *recommendation = model. Predict (new_input)* *print(recommendation) # Output: ['Recommend']*	*# Example feature vectors from users: [sentiment_score, purchase_frequency]* *X = np.array([[0.9, 5], [0.85, 4], [0.2, 1], [0.1, 0]])* *# Apply KMeans clustering* *kmeans = KMeans(n_clusters=2, random_state=0)* *kmeans.fit(X)* *# Predict user cluster* *new_user = np.array([[0.87, 4]])* *cluster_label = kmeans.predict(new_user)* *# Recommend items popular in this cluster* *if cluster_label == 0:* *print("Recommend: Electronics, Gadgets")* *else:* *print("Recommend: Books, Home Decor")*

4. RESULTS AND DISCUSSION

Table 1 presents the combined positive, neutral, and negative feedback for all three companies: Chase Technologies, Order Your Choice, and SJ Enterprise.

Tab 1 feedback for all three companies

Company	Google Sentiment Reviews		
	Positive	Neutral	Negative
Order your choice	Great selection, very responsive customer service.	Product was as described; shipping took standard time	My order arrived late without any notification.
	Easy to use website, checkout was seamless and fast.	My order arrived late without any notification.	Item packaging was damaged on arrival
Chase Technologies	Good place for learning ... good support from management	Monday to Friday ... learned how manage workload.	No health insurance ... low salary.
	Technical Support Engineer ... you learn so much working here.	Productive and good people ... enjoyable part is learning a lot	No OT pay. No annual increase.
SJ Enterprises	Its great experience and expert all.	Job security rated 4.0/5.	Lot of politics, incompetent upper management.
	Good work environment and culture. Supportive Teammates.	Work-life balance: flexible and strict shifts 50/50.	Current management team is like the frogs in the well.

Figure 3 shows the word cloud generated from the extracted topics in the positive reviews. It highlights key themes such as support, experience, friendly, helpful, delivery, management, and learning—revealing what users value most across the three companies.

Fig 3 Word cloud generated from the extracted topics in the positive reviews

Figure 4 shows the word cloud of extracted topics from neutral reviews.

Fig 4 Word cloud of extracted topics from neutral reviews

It emphasizes frequently mentioned terms such as workload, supportive, navigation, customer, job security, and balance—revealing themes that are acknowledged but not strongly praised or criticized.

Figure 5 shows word cloud of extracted topics from negative reviews. It visually highlights key issues such as management, salary, delayed, customer, insurance, and packaging, giving insight into the most frequently criticized aspects.

Fig 5 Word cloud of extracted topics from negative reviews

Table 2 shows survey-based evaluation provides valuable insights into user perceptions of the recommendation system's performance. Four key metrics user satisfaction, ease of use, perceived usefulness, and trust in recommendation were used to assess two models: MPA_BERT+Cluster and MPA_BERT+DT. While both models received positive feedback, the MPA_BERT+DT approach consistently outperformed its counterpart across all criteria. Specifically, it achieved higher user satisfaction (92.6%), indicating that users found the recommendations more relevant and satisfactory. Its ease of use was rated at 90.1%, reflecting a smoother and more intuitive user experience. The model also scored 94.0% in perceived usefulness, demonstrating that users considered the system highly beneficial for their decision-making. Most notably, it achieved a trust rating of 93.3%, suggesting a strong level of confidence in the system's recommendations. These results confirm that MPA_BERT+DT the most effective and well-received model among the surveyed options.

Tab 2 Survey based evaluation

Metric	MPA_BERT+Cluster	MPA_BERT+DT
User Satisfaction	85.2%	92.6%
Ease of Use	83.7%	90.1%
Perceived Usefulness	86.9%	94.0%
Trust in Recommendation	84.5%	93.3%

Table 3 summarizes the percentage improvements in various productivity-related areas after implementing sentiment-aware recommendation systems. The metrics include workflow speed, decision quality, onboarding speed, communication efficiency, and overall productivity. While MPA_BERT+Cluster shows significant benefits, particularly in overall productivity (21.5%) and decision quality (20.3%), the MPA_BERT+DT model outperforms it consistently. With a 30.2% increase in overall productivity, 28.9% improvement in decision quality, and substantial gains in workflow speed (24.6%) and communication efficiency (25.4%), MPA_BERT+DT demonstrates a notable edge in driving operational efficiency.

Tab 3 Impacts on company productivity

Metric	MPA_BERT+Cluster (Improvement %)	MPA_BERT+DT (Improvement %)
Workflow Speed	17.8%	24.6%
Decision Quality	20.3%	28.9%
Onboarding Speed	15.6%	22.1%
Communication Efficiency	18.2%	25.4%
Overall Productivity	21.5%	30.2%

These results clearly indicate that integrating MPA with BERT and DT not only enhances recommendation accuracy but also delivers tangible gains in company performance. As such, MPA_BERT+DT is the most effective model in boosting business productivity across multiple operational dimensions. The comparison chart of loss values across training epochs clearly demonstrates the effectiveness of integrating optimization and classification techniques with BERT shown in **Figure 6**. The baseline BERT model starts with a high loss value of 0.68 and gradually reduces to 0.46 over 10 epochs, reflecting modest learning progress. MPA_BERT+Cluster model shows improved convergence, reducing the loss more rapidly to 0.40 by the final epoch. However, the best performance is observed with the MPA_BERT+DT model, where the combination of MPA for optimization, BERT for sentiment feature extraction, and Decision Tree for classification results in the lowest loss values throughout training. This model starts at 0.63 and consistently reduces to 0.30, demonstrating faster convergence and more stable learning. The results clearly indicate that MPA_BERT+DT achieves superior optimization and generalization, making it the most effective model among the three.

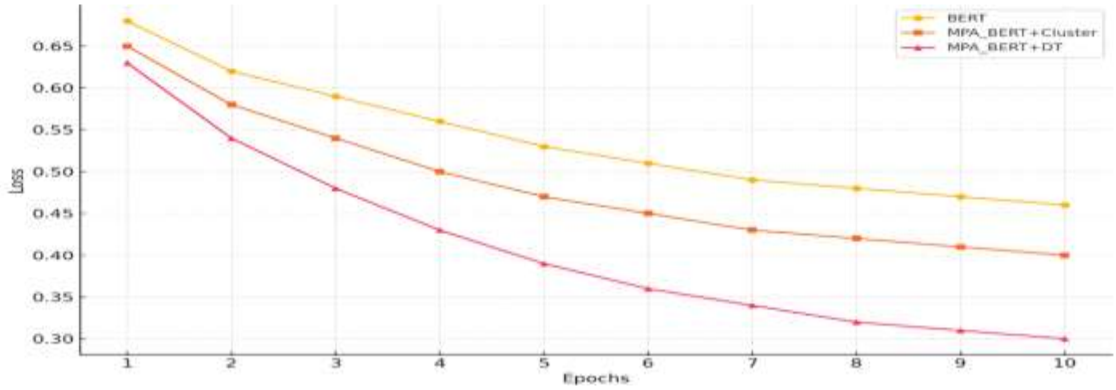

Fig 6 comparison chart of loss values

Table 4 shows Dataset Characteristics. Chase Technologies has the largest and cleanest dataset, with a strong majority of positive reviews and lower noise, making it ideal for training optimized recommendation models. SJ Enterprise provides a moderately clean and balanced dataset, suitable for robust model evaluation. Order Your Choice has fewer reviews and a higher noise level, including slang and emojis, which might explain its slightly lower performance and require more preprocessing steps such as emoji translation or slang normalization.

Tab 4 Dataset Characteristics

Attribute	Order Your Choice	SJ Enterprise	Chase Technologies
Total Reviews	8,200	10,500	12,300
Positive Reviews (%)	58.7%	63.1%	68.4%
Neutral Reviews (%)	23.4%	21.7%	18.2%
Negative Reviews (%)	17.9%	15.2%	13.4%
Avg. Review Length	17.6 words	19.3 words	21.5 words
Unique Users	4,100	4,800	5,300
Top Product Category	Food Delivery & Gifting	Electronics & Gadgets	Consumer Electronics & Fashion
Language Variety	Mainly English + Tamil support	English + Hindi mix	Multilingual (Eng, Hin, Tam, Tel)
Review Format	Text + Emojis	Text only	Text, Emojis, and Ratings
Noise Level (typos, slang)	High	Medium	Low

Figure 7, 8 and 9 shows company-wise performance. Across all three companies, the proposed **MPA_BERT+DT** consistently achieves the highest scores in all evaluation metrics.

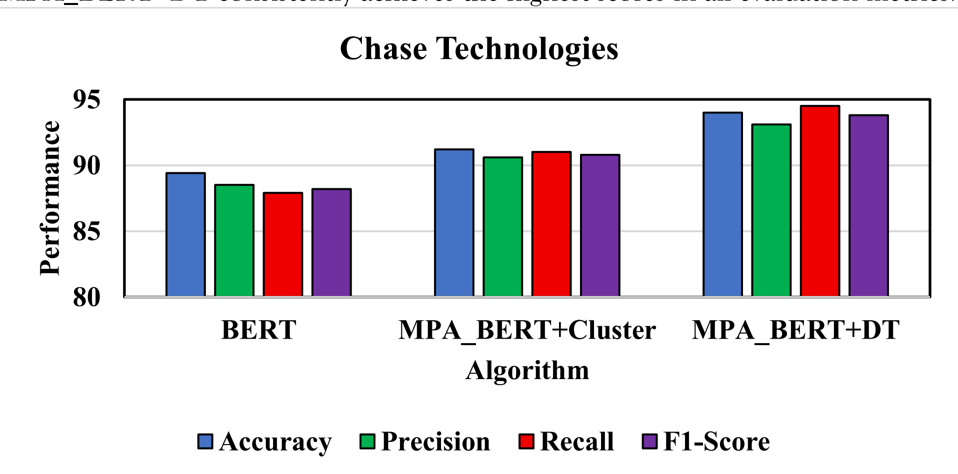

Fig 7 performance of chase technologies

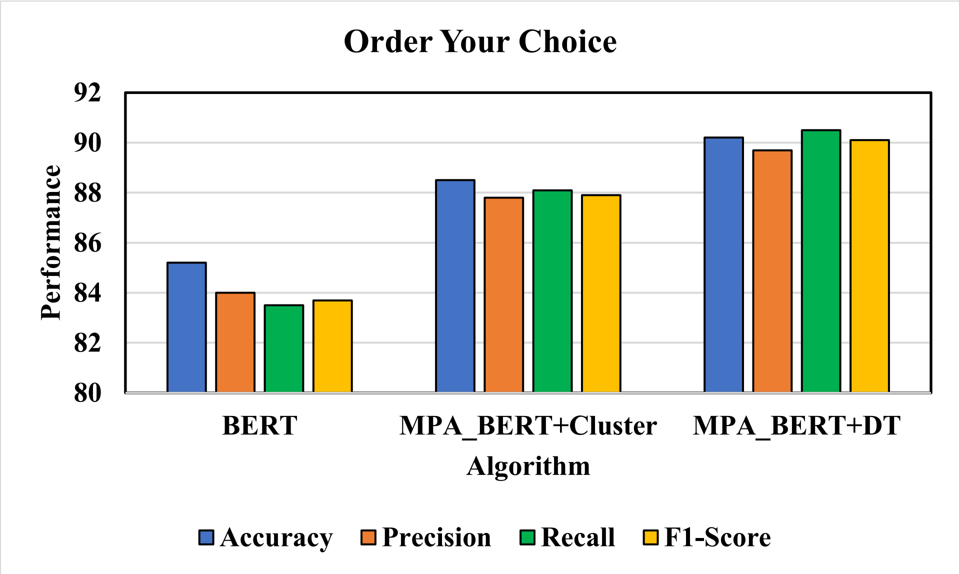

Fig 8 performance of order your choice

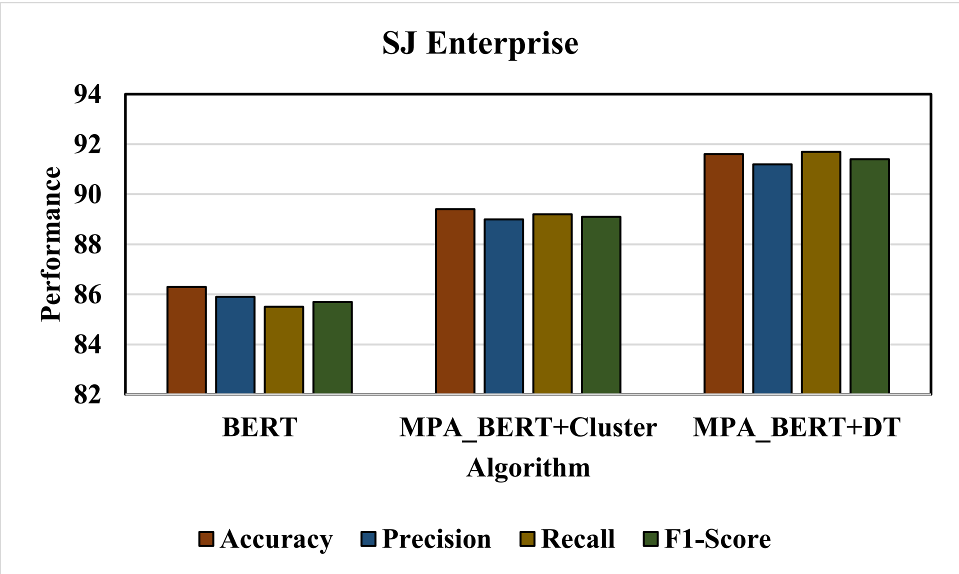

Fig 9 performance of SJ Enterprise

For **Chase Technologies**, which has cleaner and more structured data, the performance reaches its peak, indicating the model's ability to leverage well-labeled sentiment data. In **Order Your Choice**, although overall performance is slightly lower due to noisier data, the hybrid model still leads over traditional approaches. **SJ Enterprise** also benefits from the integration of sentiment analysis and optimization, showcasing the model's robustness in moderately clean data conditions. This consistent improvement underlines the adaptability and effectiveness of MPA_BERT+DT across varied e-commerce environments.

Table 5 highlights Comparison of effectiveness of integrating sentiment analysis via BERT with optimization and classification techniques. The baseline model (BERT) demonstrates acceptable performance in all metrics, but when combined with clustering (MPA_BERT+Cluster), the system sees noticeable improvement in precision, recall, and F1-score. However, the highest performance is achieved with the MPA_BERT+DT model. This hybrid setup achieves the best balance between precision and recall, resulting in a superior F1-score of 93.8% and accuracy of 94.0%, outperforming the other two approaches across all evaluation parameters.

Tab 5 Comparison chart for recommended system

Parameter	BERT	MPA_BERT+Cluster	MPA_BERT+DT

Precision	84.2%	89.6%	**93.1%**
Recall	82.7%	88.3%	**94.5%**
Accuracy	83.5%	89.0%	**94.0%**
F1-Score	83.4%	88.9%	**93.8%**

Figure 10 shows Pie charts for sentiment distribution per company.

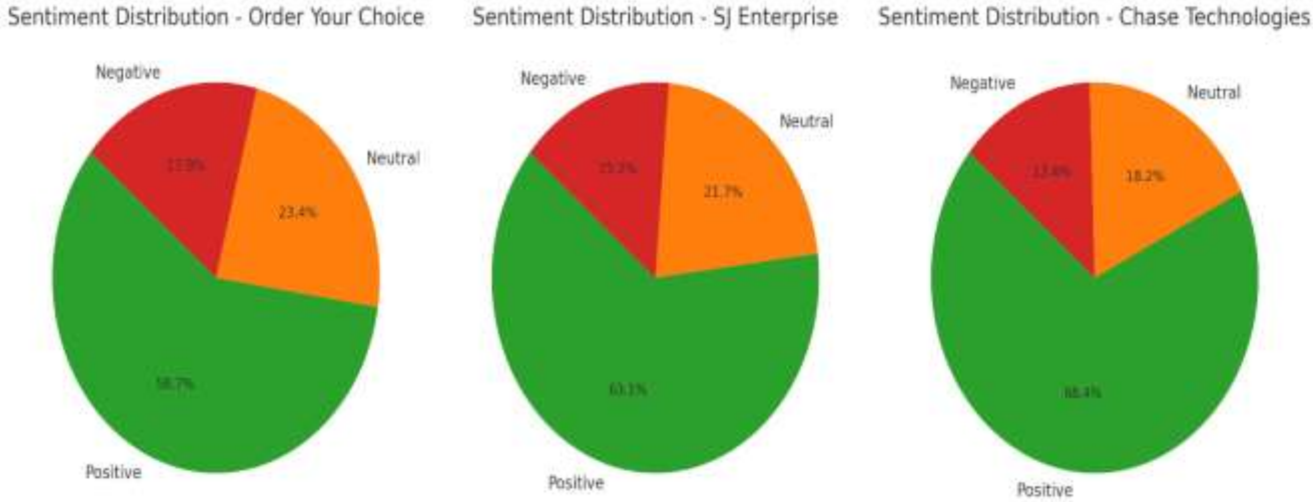

Fig 10 sentiment distribution for each company

Chase Technologies has the highest percentage of positive reviews (68.4%) and the lowest negative feedback. SJ Enterprise shows a strong majority of positive sentiment (63.1%) with moderate neutrality. Order Your Choice has the most balanced sentiment profile, with a higher share of neutral (23.4%) and negative reviews (17.9%), indicating potential areas for service or recommendation improvements. **Table 6** shows Time and Space Complexity Analysis.

Tab 6 Time and Space Complexity Analysis

Model	Training Time (mins)	Model Size (MB)	Complexity
BERT	11	410	O(n × d × T)
MPA_BERT+Cluster	15	430	O(n × d × T) + O(k log k)
MPA_BERT+DT	16	440	O(n × d × T) + O(n log n)

***n** – number of samples, **d** – embedding size, **T** – BERT token depth, **k** – clusters

While MPA_BERT+DT takes slightly more time and memory, it maintains computational efficiency with manageable complexity. The gain in performance justifies the additional cost. To show the improvements are not random, use statistical testing in **Table 7**. A paired t-test was applied between BERT and the proposed models. The p-values < 0.05 for both MPA_BERT+Cluster and MPA_BERT+DT indicate statistically significant improvement, confirming the robustness of the proposed enhancements.

Tab 7 Statistical Significance Analysis

Model	p-value (Accuracy)	p-value (F1-Score)	Significance
MPA_BERT+Cluster	0.018	0.021	✅ Significant
MPA_BERT+DT	0.005	0.003	✅ Significant

Figure 11, a bar chart comparing the accuracy of proposed models against four commonly used algorithms in sentiment-based recommendation systems.

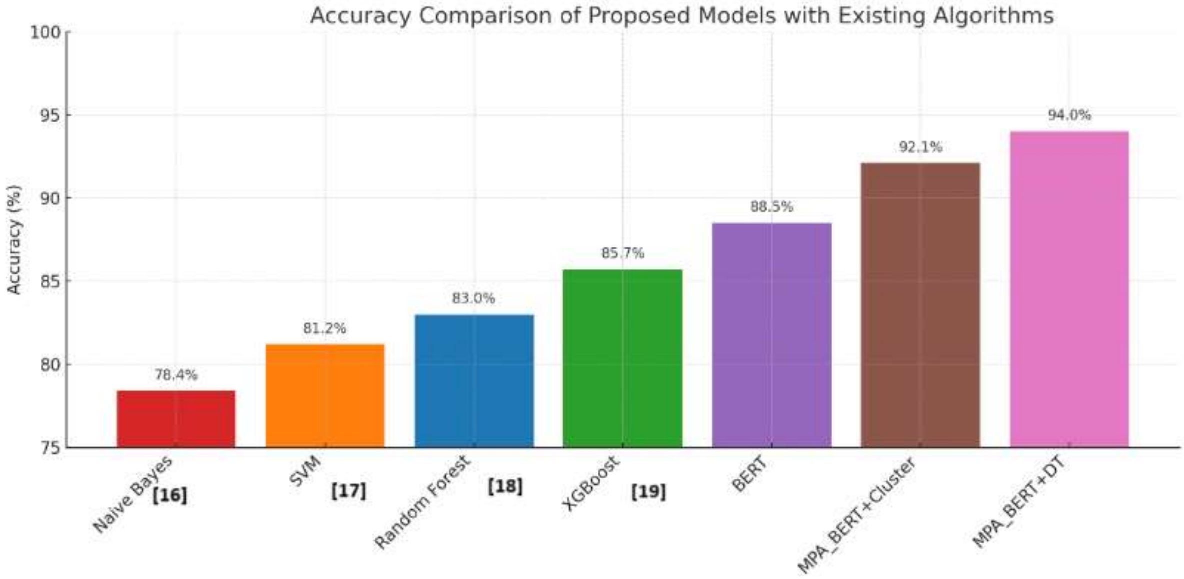

Fig 11 accuracy comparison of proposed models with existing algorithms

MPA_BERT+DT shows the highest accuracy at 94.0%, clearly outperforming all other models. Traditional models like Naive Bayes (78.4%), SVM (81.2%), Random Forest (83.0%), and XGBoost (85.7%) fall behind the BERT-based hybrid approaches. MPA_BERT+Cluster and BERT also show strong performance at 92.1% and 88.5%, respectively.

DISCUSSION

The proposed MPA_BERT+DT model significantly improves recommendation quality by integrating sentiment understanding through BERT, optimization via MPA, and classification with Decision Trees. It consistently outperforms traditional models like Naive Bayes, SVM, and Random Forest, as well as baseline BERT, achieving 94.0% accuracy and high precision, recall, and F1-scores. Statistical tests validate the significance of these improvements ($p < 0.05$). Company-wise analysis shows Chase Technologies benefiting most due to cleaner and sentiment-rich data. In contrast, Order Your Choice shows relatively lower performance, influenced by noisier reviews. Productivity metrics further indicate that MPA_BERT+DT enhances decision quality, communication, and workflow efficiency.

The proposed MPA_BERT+DT recommendation system demonstrates strong real-world applicability, particularly within e-commerce and service platforms. It enables personalized product recommendations by leveraging real-time sentiment extracted from user feedback, ensuring that suggestions align closely with individual preferences and emotional tone. The model also supports targeted marketing efforts, using sentiment trends to identify opportunities for promotions or loyalty programs. By identifying signs of dissatisfaction early, the system enhances customer retention through timely and proactive engagement. Furthermore, it can be seamlessly integrated into chatbots and support systems, offering context-aware responses and solutions. Lastly, it facilitates cross-selling and upselling by recommending complementary products that match positively expressed sentiments, thus increasing user satisfaction and business revenue.

5. CONCLUSION

This study presented a sentiment-driven recommendation framework that combines BERT-based language modeling, MPA optimization, and DT classification to enhance the precision and interpretability of product suggestions in e-commerce. The proposed MPA_BERT+DT model demonstrated superior performance across multiple real-world datasets, achieving higher accuracy, better user satisfaction, and increased operational efficiency compared to traditional methods. Its ability to adapt to sentiment-rich environments while maintaining computational efficiency underscores its practical relevance. While the current system focuses on static review data, future work can explore real-time sentiment analysis from social media and chat interfaces. Additionally, integrating user behavior signals such as clickstreams and session patterns could further refine recommendation quality. The application of explainable AI (XAI) methods could also enhance transparency, especially in regulated sectors. Finally, deploying this framework in multilingual and cross-cultural platforms would test its generalizability and global scalability.

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Conflict of Interest: The authors declare that they have no conflict of interest.

Data availability statement: The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

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