International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 2049-2053
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0274

Emotion to Purchase Conversion Model for E-commerce System

Ms. P. Mallika[1], Dhivya T[2], Mina Fathima A[3], Shalini P[4], Sowmiya [5]
[1] Assistant Professor (Sr. G), Department of Artificial Intelligence and Data Science, Jai Shriram Engineering College, Tirupur, Tamil Nadu, India
[2,3,4,5] UG Scholar, Department Of Artificial Intelligence And Data Science, Jai Shriram Engineering College, Tirupur, Tamil Nadu, India
Emails:*mallika@jayshriram.edu.in[1],dhivyadhiv01@gmail.com[2],minafathima04@gmail.com[3],shalinipalanisamy27@gmail.com[4],kumarsowmiya74@gmail.com[5]*

Abstract
The overwhelming development of e-commerce sites has brought with it greater use of smart personalization to boost customer satisfaction and purchase conversion rates. Historical user behaviour and collaborative filtering are the key methods looked upon to make traditional recommendation system, whenever real-time search intent, emotional signals in product reviews are disregarded. The proposed paper presents a proposal of an Emotion-to-Purchase Conversion Model which will combine intent detection based on Bidirectional Encoder Representations with Transformers (BERT) and sentiment analysis based on a Multinomial Naive Bayes classification with a Random Forest-based fake review filtering mechanism in a hybrid recommendation system. The model lexically derives emotional polarity on the text of product reviews and contextual search intent on the query entered by users which are combined with the help of weighted ensemble ranking technique. Based on Python, Scikit-learn, Transformers, and Streamlit, the system can recreate a real-time e-commerce setting and has explainable AI traits such as voice-based recommendation explanations. The results of the experiment prove an increase in the potential rate of conversion, emotional consistency, and more adequate recommendations in reference to the traditional ones, which can be utilized in order to create more efficient and user-oriented online shopping experiences. The framework will be very flexible to the changing preferences of the users which makes it suitable to intelligent recommendation systems in future.
***Keywords**: Naive Bayes, Random Forest, Hybrid Filtering, Natural Language Processing, Explainable AI, Purchase Conversion, Personalized Recommendation, Fake Review Detection.*

1. Introduction
The e-commerce platforms such as Amazon, Flipkart, and Alibaba manage millions of products that belong to different categories and this makes it difficult to locate what one wants. The number of options that are available in digital markets is often very large and is increasingly growing, which leads to decision fatigue and lower levels of satisfaction in customers. In response to this issue, recommender systems that aim to increase user experience and design product deals that are more personal have become an important part of modern e-commerce infrastructures. The main staple of traditional methods of recommendation is popularity-based ranking methods, content-based filtering, and collaborative filtering. Whereas content-based filtering implies the recommendation of products using the similarities between user profile and product attributes, collaborative filtering assumes that the user preferences can be predicted according to the similarities between people or products. .These are the problems with cold-starting new users or goods, over-relying on previous interaction data, the inability to adapt to the needs of new users, and the inability to effectively interpret search intent in real time. More importantly, the realm of emotional intelligence is not present in conventional systems. Since most product reviews are in terms of satisfaction, dissatisfaction, trust, enthusiasm, or disappointment, the affective aspects play an important role in influencing consumer decision-making. But most of the recommendation systems in

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 2049-2053
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0274

operation today do not take into account the rich contextual and emotional content of textual remarks, instead preferring to utilize numerical ratings alone. This exclusion can result in the suggestion of high average rated goods with poor user experiences. To avoid these constraints, this paper will suggest an advanced recommendation architecture that combines real-time intention recognition and sentiment-based ranking. The approach is based on a hybrid ranking algorithm to make suggestions that are straightforward to understand following the analysis of user intent on search queries and evaluation of the emotional polarity of product ratings. The combination of contextual and emotional intelligence leads to higher levels of overall client satisfaction by reducing the chances of mismatched recommendations [1].

2. Related Work

2.1. Collaborative Filtering

Collaborative filtering is one of the oldest recommendation systems that has been used extensively. Resnick et al were the initial proponents of this approach towards predicting consumer preference by making comparisons across users or objects. It is based on the principle that the users who have shown similar behavior in the past would show similar interests in future.

2.2. Content-Based Filtering

Pazzani and Billsus recommended content-based filtering as an alternative mechanism which recommends products based on user profiles and product characteristics. This technique is used to compare the features of the items to user preference that is acquired through previous interactions. Due to the constant exposure of users to similar types of products, content-based systems do not necessarily have diversity and cannot be discovered, despite their ability to effectively personalize recommendations to individual users [3].

3. Method

The proposed model is an Emotion-to-Purchase Conversion Model, which is an amalgamation of sentiment-sensitive ranking and real-time intent detection in a hybrid recommendation system. The proposed architecture enhances the accuracy of personalization and purchasing decision probability because it incorporates the contextual knowledge and emotional validation, unlike the traditional recommender systems that largely rely on the previous actions or numerical score shown in the Figure 1.

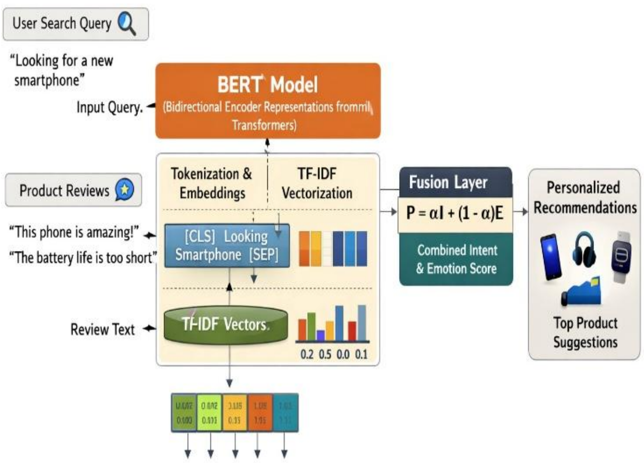

Figure 1 **Bert Model Workflow In EPCM**

The system consists of six important components:

- Data Preparation and Data Collection.
- Module for Intent Detection
- Sentiment Analysis Module.
- normalization of scores and engineering characteristics.
- Weighted Ranking System Hybrid.
- Recommendations Interface.

3.1. Data Collection & Processing

The three primary sources of data utilized by the proposed system are user search queries, product metadata (title, category, price, and features), and product reviews along with ratings. Preprocessing operations are lowercase text conversion, removal of stop words and other special characters, tokenization and lemmatization of words to standardize the appearance of words The cleaned review texts are then translated to numerical representations and processed by means of the Term Frequency Inverse Document Frequency (TF-IDF) vectorization to create a sentiment classification. An 80:20 split is then applied to the dataset to form a training and testing dataset to provide credible model evaluation and generalization performance [2].

IRJAEH

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 2049-2053
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0274

3.2.Intent Detection Module

The Intent Detection Module is intended to accurately identify the underlying buy intentions through interpretation of the search queries of the user in real time. The traditional search algorithms that are based on keys often involve the exact word matching, which lacks semantic connections and context meaning in search. To overcome this limitation, the proposed approach employs a transformer-based deep learning model, that is, Bidirectional Encoder Representations with Transformers (BERT), to achieve a contextual understanding. First, the tokenizer, which is the BERT tokenizer, tokenizes the search queries that users have posted, converting the input text into tokens which are compatible with the already trained model. The module produces an Intent Score (In), a normalized number in the interval of 0 to 1 that reflects the compatibility of a particular product with a query put by the user. This score is then applied in the hybrid ranking [8].

3.3.Fake Review Detection Module.

Fake Review Detection Module is a necessary preprocessing unit of the proposed system, which guarantees that the reviews of the products on which the sentiment analysis and the ranking of recommendations are based are authentic and reliable. In the environment of real e-commerce services, a considerable percentage of product reviews are either fake or bribed, and as a result, artificially inflated sentiment scores are obtained, distorting the true quality of the products and deceiving consumers. To overcome this limitation, the proposed system will use a Random Forest classifier that is trained to classify authentic and fake reviews on the basis of a range of extracted stylometric, linguistic, and behavioral characteristics[7].

3.4.Sentimental Analysis Module

In order to determine the overall consumer happiness, the Sentiment Analysis Module is entrusted with the task of judging the emotional polarity expressed in product reviews. A Multinomial Naive Bayes classifier is used in the system and it was trained on review text feature representations of Term Frequency-Inverse Document Frequency) TF-IDF. The preprocessing steps of the product reviews include lemmatization, tokenization [9], removal of stop words, and text normalization. The overall emotional rating of a product, a Sentiment Score (S_s), is computed in the following way:

$$S_s = \frac{\text{Number of Positive Reviews}}{\text{Total no of reviews}}$$

This formulation yields a normalized score that is between 0 and 1; higher numbers indicate a more positive sentiment of customers.

3.5.Score Normalization

Both values are normalized to ensure a uniform range of values and fair and balanced combination of intent and sentiment ratings in the hybrid ranking process [10].

The normalized Intent Score (□□′) is determined by:

The formula, $$Is' = \frac{Is - Imin}{I\,max - Imin}$$

Similarly, the normalized Sentiment Score (Ss) is calculated in the following way:

$$Ss' = \frac{Ss - Smin}{Smax - Smin}$$

where I min and I max are established by represent the minimal and maximal intent rating of each product, and Smin.

3.6.Hybrid Weighted Ranking System

The final recommendation score is obtained by a weighted summation approach that is an integration of the normalized intent, sentimental and collaborative similarity scores into one ranking value. The aggregate score is calculated as:

$$\textbf{Final Score} = \alpha Is' + \beta Ss' + \gamma Cs$$

As an example, we can look at a product recommendation case where normalized intent score, which the BERT-based intent detection module has calculated, is 0.85, which means that the purchase intent is high, normalized sentiment score is 0.75, which means that overall customer feedback is mostly positive and collaborative similarity score is 0.65. Using the weights coefficients of 0.4, 0.35 and

International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 04 Issue: 04 April 2026
Page No: 2049-2053
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2026.0274

0.25 (where 0.4 + 0.35 + 0.25 = 1) the weighted recommendation score will be 0.765. This is the sum of the scores which are then compared to the other candidate items where a higher score means a greater priority which is to be recommended.

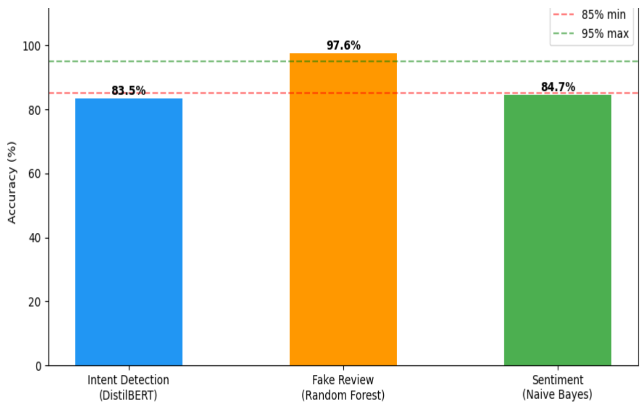

Figure 2 Model Accuracy Comparison

3.7. Interface For Explainable Recommendations

The Explainable Recommendation Interface, which provides brief descriptions of each of the proposed products, will enhance openness, confidence in the user, and confidence in decision making. The proposed approach generates human friendly understandings of the reasons why a particular product is on the recommended list unlike in the traditional systems of recommendation where the results would be displayed without an explanation. These justifications are based on the key ranking variables intent alignment, sentiment score and collaborative similarity[5].

4. Results and Discussion

4.1. Results

The suggested Emotion-to-Purchase Conversion Model was tested on an e-commerce product review sample that was preprocessed with tokenization, stop words, and lemmatization and divided into training (80 percent) and testing (20 percent) subsets. The Multinomial Naive Bayes-based Sentiment Analysis Module was able to classify product reviews according to positive, negative, and no sentiment, and its results were evaluated based on Precision, Recall and F1-Score with the highest performance of the positive sentiment classification, which means that the TF-IDF feature representations are capable of extracting emotional polarity in review text [4].

4.2. Discussion

The findings of the suggested Emotion-to-Purchase Conversion Model prove that the consideration of emotional intelligence and semantic intent within recommendations framework yields considerably more effective results than the traditional recommendations strategies. The Multinomial Naive Bayes Sentiment Analysis Module is effective in capturing emotional polarity among product review in terms of TF-IDF feature representations, and shows high Precision, Recall, and F1-Score among all the sentiment classes, which proves that lexical features of product review based on user-generating text are valid predictors of consumer satisfaction. The Intent Detection Module based on BERT was able to produce correct normalized Intent Score by getting to the full contextual meaning of user search queries which affirms the fact that transformer-based semantic embeddings are better at detecting real-time purchase intent than traditional methods based on key-word matching semantic detectors. The integrity of the sentiment-based ranking was enhanced by the Random Forest Fake Review Detection Module, which is reliable to filter out fake reviews in order to carry out sentiment aggregation and avoid the occurrence of artificially inflated scores that will corrupt the recommendation output. A weighted combination of intent, sentiment and collaborative similarity scores via an optimized weighted formula, the Hybrid Weighted Ranking System calculated final recommendation ranking that was more precise and purchase consistent compared to any single signal recommendation method, thus confirming that the multi-signal architecture is fundamental to the delivery of emotionally consistent and user-oriented e-commerce recommendation [6].

Conclusion

The Emotion-to-Purchase Conversion Model to be presented as a part of the given research merges a sentiment-aware ranking with transformer-based intent detection into a hybrid recommendation system. The proposed approach enhances the quality of personalization compared to the traditional behavior-based systems because it combines the effects of emotional validation and contextual semantic understanding.

Acknowledgements

The authors indicate that they are appreciating to all and all organizations that have facilitated their study project on the Emotion-to-Purchase Conversion Model to the E-commerce Systems. We also have great references to our instructors and mentors who were alongside us during our project work, provided their recommendations and suggestions as well as feedbacks at every stage of the project. We also wish to express our heartfelt thanks to research community who have managed to create the ground work and give impetus to our study through their past work in the area of sentiment analysis, intent detection, recommendation systems, and e-commerce personalization.

References

[1]. D. Roy and M. Dutta, "A systematic review and research perspective on recommender systems," Journal of Big Data, vol. 9, no. 59, 2022.

[2]. Y. Gong, "Research on recommendation algorithm based on user sentiment analysis," Applied and Computational Engineering, vol. 45, pp. 84–91, 2024.

[3]. S. Saxena and B. Bhushan, "Transformers (BERT)-based framework for web recommendations using sentiment-enriched data," Journal of Information Systems Engineering and Management, 2025.

[4]. H. U. Khan, A. Naz, and F. K. Alarfaj, "A transformer-based architecture for collaborative filtering modeling in personalized recommender systems," Scientific Reports, vol. 15, 2025.

[5]. D. Lim and T. Lee, "Enhanced recommender system with sentiment analysis of review text and SBERT embeddings," Mathematics, vol. 14, no. 1, 2026.

[6]. Li, K. Liu, and X. Chen, "A context-aware personalized recommendation framework integrating user clustering and BERT-based sentiment analysis," Preprints, 2025.

[7]. "Integrated sentiment analysis with BERT for enhanced hybrid recommendation systems," Expert Systems with Applications, 2024.

[8]. E. Hasan et al., "Review-based recommender systems: A survey of approaches, challenges and future perspectives," arXiv preprint arXiv:2405.05562, 2024.

[9]. Y. Zhao et al., "Recommender systems in the era of large language models," arXiv preprint arXiv:2307.02046, 2023.

[10]. Y. Deldjoo et al., "A review of modern recommender systems using generative models," arXiv preprint arXiv:2404.00579, 2024.