BINARY SENTIMENT ANALYSIS AND SENTIMENT MARKETING STRATEGY OPTIMIZATION OF E-COMMERCE PLATFORM USER COMMENTS BASED ON DEEP LEARNING ALGORITHM

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SUMMARY

Binary sentiment analysis plays a crucial role in e-commerce marketing strategy optimization by classifying user comments into positive or negative sentiments, allowing businesses to analyze customer feedback, predict user behavior, and enhance personalized marketing efforts. This paper explores the application of the bi-gram Hidden Markov Optimization (bi-gram HMMO) model in sentiment analysis within e-commerce platforms in China. Leveraging natural language processing techniques, the bi-gram HMMO model captures intricate dependencies between consecutive words to discern user sentiment from textual data such as reviews and comments. Through a systematic analysis of user interactions, the model accurately identifies and categorizes emotional states, providing valuable insights into customer satisfaction levels and areas for improvement. BERT + JOA achieved a 95.6% accuracy and a 95.4% F1-score, outperforming traditional models like Bi-gram HMM (78.5%) and CNN + JOA (91.5%). Sentiment-aware marketing strategies lead to higher customer engagement, conversion rates, and revenue growth. After implementing sentiment-optimized strategies, customer conversion increased by 73.3% (from 4.5% to 7.8%), while customer retention improved by 24.9% (from 55.2% to 68.9%). Click-through rates (CTR) doubled (+103.1%), and sentiment-based product recommendations saw a 136.6% increase in engagement, indicating that customers respond better to personalized and emotionally intelligent marketing campaigns. Additionally, monthly revenue growth surged by 127.0%, while the average order value (AOV) increased by 33.4% (from $52.3 to $69.8), demonstrating that sentiment-aware marketing strategies directly influence e-commerce profitability. The findings reveal a prevalence of positive sentiment in user expressions, particularly towards product quality, delivery speed, and customer service, with probability scores ranging from 0.75 to 0.90. Conversely, instances of negative sentiment are associated with product defects or damaged items, yielding lower probability scores of 0.60 to 0.80.

KEY WORDS: Emotional marketing, E-commerce, Hidden markov model, Bi—gram, Deep learning, Optimization

1. INTRODUCTION

Sentiment analysis of user reviews and the implementation of emotional marketing strategies on e-commerce platforms represent two pivotal dimensions in understanding and influencing consumer behavior in the digital realm [1]. The integration of sentiment analysis techniques [2] allows businesses to decipher the underlying emotions and opinions expressed within user-generated content such as product reviews, comments, and social media interactions [3]. By leveraging natural language processing algorithms, sentiment analysis categorizes user sentiments as positive, negative, or neutral, providing businesses with valuable insights into customer satisfaction, preferences, and pain points [4]. Moreover, emotional marketing strategies capitalize on these insights to craft tailored marketing campaigns that resonate with consumers on an emotional level [5–7]. By understanding the emotional triggers that drive purchasing decisions, businesses can create compelling narratives, visuals, and messaging that evoke desired emotional responses from their target audience. With feelings of joy, excitement, trust, or nostalgia, emotional marketing aims to forge deeper connections with consumers, fostering brand loyalty and driving conversions [8–10]. The synergy between sentiment analysis and emotional marketing strategies empowers e-commerce platforms to create personalized and emotionally resonant experiences for their customers. By integrating sentiment analysis insights into their marketing strategies, businesses can deliver more relevant and impactful messaging, products, and services, thereby enhancing overall customer satisfaction and loyalty [11–12]. As e-commerce continues to evolve, leveraging data-driven approaches to understand and influence consumer emotions will remain essential for staying competitive and fostering long-term success in the digital marketplace [13]. In the dynamic landscape of e-commerce, where user reviews wield significant influence over consumer decisions, optimizing sentiment analysis holds the key to unlocking invaluable insights for businesses [14–15]. Leveraging the power of deep learning algorithms, this paper delves into the realm of sentiment analysis and emotional marketing strategies within the context of e-commerce platforms. By harnessing the capabilities of deep learning, businesses can delve deeper into the nuanced sentiments expressed in user reviews, gaining a profound understanding of customer preferences, satisfaction, and pain points [16–17]. Furthermore, the integration of emotional marketing strategies allows businesses to not only interpret sentiments but also tailor their marketing efforts to evoke desired emotional responses from their audience [18]. Through the synthesis of cutting-edge technology and emotional intelligence, this paper explores how businesses can effectively utilize deep learning algorithms to optimize sentiment analysis and craft emotionally resonant marketing strategies, thereby enhancing customer engagement, and loyalty, and ultimately, driving success in the competitive e-commerce landscape.

In the realm of e-commerce, where user reviews wield immense influence over purchasing decisions, leveraging advanced technologies like deep learning algorithms holds immense promise for businesses aiming to optimize sentiment analysis and enhance emotional marketing strategies [19–21]. Deep learning, a subset of artificial intelligence, empowers businesses to delve into the intricate nuances of user feedback, transcending mere positive and negative classifications to understand the underlying emotions and sentiments expressed. By employing sophisticated neural networks such as Recurrent Neural Networks (RNNs) and Transformers, companies can extract rich insights from vast repositories of textual data, discerning not just what customers say but how they feel. This deep understanding of sentiment forms the foundation for crafting emotionally resonant marketing strategies [22–23]. Emotional marketing, driven by the recognition that consumer decisions are often rooted in feelings rather than logic, seeks to evoke specific emotions that forge strong connections between brands and consumers. By aligning marketing efforts with the sentiments unearthed through deep learning-powered sentiment analysis, businesses can create campaigns that resonate deeply with their target audience, fostering trust, loyalty, and brand advocacy [24–25]. Furthermore, the integration of deep learning algorithms and emotional marketing strategies enables a dynamic feedback loop, wherein insights gleaned from user reviews inform the creation of emotionally intelligent marketing campaigns, which in turn shape future consumer sentiment [26]. This iterative process facilitates continuous improvement, allowing businesses to adapt swiftly to evolving customer preferences and market trends.

The investigation and implementation of the bi-gram Hidden Markov Optimization (bi-gram HMMO) model for e-commerce platform sentiment analysis constitute the main contribution of this work. With the help of this advanced model, which can detect complex word relationships, we have extracted useful information on user mood from textual sources like reviews and comments. Businesses may use the actionable insights provided by our research to improve user experience and promote growth by better understanding customer perceptions and satisfaction levels within e-commerce settings. To optimize e-commerce marketing strategies, the bi-gram model uses binary sentiment analysis with the help of the BERT + Jellyfish Optimization Algorithm (JOA). The proposed approach achieves a 95.6% accuracy and a 95.4% F1-score, outperforming traditional models such as Bi-gram HMM (78.5%), LSTM + JOA (92.0%), and CNN + JOA (91.5%). Incorporating JOA effectively optimizes model hyperparameters, resulting in a 16.8% increase in marketing sales impact, compared to 5.1% at early training stages (epoch 5). From a marketing perspective, sentiment-driven strategies enhance key performance indicators. The customer conversion rate increased by 73.3% (from 4.5% to 7.8%), while customer retention improved by 24.9% (from 55.2% to 68.9%). User engagement also saw a substantial 46.8% rise in average time spent on the platform (from 6.2 to 9.1 minutes), with a 32.1% reduction in bounce rate (from 41.7% to 28.3%). Furthermore, click-through rates (CTR) more than doubled (+103.1%), and sentiment-based product recommendations saw a 136.6% increase in engagement. These improvements translated into a 127.0% growth in monthly revenue, with the Average Order Value (AOV) rising by 33.4% (from $52.3 to $69.8).

2. RELATED WORKS

The referenced studies offer a comprehensive exploration of sentiment analysis within the realm of e-commerce, focusing on leveraging advanced techniques, particularly deep learning algorithms, to extract valuable insights from user reviews. These works span a variety of methodologies and approaches, reflecting the diverse strategies employed by researchers to enhance sentiment analysis and its applications in the e-commerce domain. Several studies, such as Rasappan et al. (2024) and Yang et al. (2020), delve into the development of intelligent systems and hybrid deep learning models specifically tailored for sentiment analysis of e-commerce product reviews. These models often incorporate innovative techniques for term weighting, feature selection, and sentiment lexicon construction to improve the accuracy and robustness of sentiment classification. Others, like Loukili et al. (2023) and Chandio et al. (2022), explore the application of machine learning algorithms for sentiment analysis in e-commerce, focusing on recommendation systems and sentiment analysis of Roman Urdu, respectively. These studies highlight the importance of considering linguistic and cultural nuances in sentiment analysis for diverse user bases and languages.,Furthermore, research by He et al. (2022) and Vatambeti et al. (2024) examines the fusion of sentiment analysis with other factors, such as product experience and social media data (e.g., Twitter), to provide a more comprehensive understanding of consumer sentiment and behavior in the e-commerce ecosystem.

Moreover, the studies by Zhang (2020), Arobi et al. (2022), and Lin (2020) delve into the application of deep learning techniques, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for sentiment analysis of e-commerce reviews. Lin (2020) delves into sentiment analysis of e-commerce customer reviews, employing natural language processing (NLP) techniques to extract insights from textual data. The study likely explores methodologies for analyzing the sentiments expressed in customer reviews and understanding their implications for businesses operating in the e-commerce sector. On a similar note, Cao et al. (2023) contribute to the field by focusing on sentiment analysis of online reviews and its potential for informing product feature improvements using deep learning techniques. Their work likely investigates how deep learning models can be trained to effectively analyze and classify sentiments in online reviews, providing valuable insights for product development and enhancement strategies. Chandio et al. (2022) tackle sentiment analysis within a specific linguistic context, focusing on Roman Urdu in e-commerce reviews and employing machine learning algorithms for analysis. Their study likely addresses the challenges and opportunities in sentiment analysis for languages with specific linguistic characteristics, offering tailored solutions for analyzing sentiments in Roman Urdu e-commerce reviews. Furthermore, Pons-Muñoz de Morales (2020) explores the intersection of big data analytics and sentiment analysis in predicting consumer behavior based on e-commerce platform reviews. Their work likely examines methodologies for extracting meaningful insights from large volumes of review data to anticipate consumer preferences and trends, thereby informing strategic decision-making for businesses. Lastly, Chamekh et al. (2022) contribute to the advancement of sentiment analysis in e-commerce through their exploration of deep learning-based approaches. Their study likely investigates the application of deep learning models for sentiment analysis tasks, aiming to enhance the accuracy and efficiency of sentiment analysis in the e-commerce domain.

Some studies, like Rasappan et al. (2024) and Yang et al. (2020), focus on developing intelligent systems and hybrid deep learning models tailored specifically for sentiment analysis of e-commerce product reviews, often integrating innovative techniques for improved accuracy and robustness. Others, such as Loukili et al. (2023) and Chandio et al. (2022), explore the application of machine learning algorithms for sentiment analysis in e-commerce, addressing linguistic and cultural nuances for diverse user bases and languages. Additionally, research by He et al. (2022) and Vatambeti et al. (2024) investigates the fusion of sentiment analysis with factors like product experience and social media data to gain a comprehensive understanding of consumer sentiment and behavior. Moreover, studies by Zhang (2020), Arobi et al. (2022), and Lin (2020) delve into deep learning techniques like CNNs and RNNs for sentiment analysis of e-commerce reviews, focusing on methodologies for extracting insights from textual data and informing product development strategies. Chandio et al. (2022) address sentiment analysis in a specific linguistic context, focusing on Roman Urdu in e-commerce reviews, while Pons-Muñoz de Morales (2020) explores big data analytics and sentiment analysis to predict consumer behavior based on e-commerce platform reviews. Finally, Chamekh et al. (2022) contribute to sentiment analysis advancement in e-commerce through deep learning-based approaches, aiming to enhance accuracy and efficiency in sentiment analysis task.

3. BINARY SENTIMENTAL ANALYSIS WITH MARKETING STRATEGY FOR E-COMMERCE

User sentiment analysis in e-commerce involves the intricate process of understanding and categorizing the sentiments expressed in user-generated content, such as product reviews and comments, within online shopping platforms. Leveraging mathematical frameworks, particularly machine learning algorithms, enables businesses to effectively quantify and interpret these sentiments, providing valuable insights into customer experiences and preferences. At the core of sentiment analysis lies the sentiment classification equation, which serves as the mathematical representation of the model's decision-making process. In its essence, this equation encapsulates the relationship between the features extracted from user-generated content and the predicted sentiment labels. These features, derived through techniques like natural language processing, encompass various aspects of the text, such as word frequency, context, and sentiment indicators. The sentiment classification equation can be expressed as in equation (1)

$$f(x) = sign(\omega_0 + \omega_1 x_1 + \omega_2 x_2 + \cdots + \omega_n x_n) \tag{1}$$

In equation (1) $f(x)$ denotes the predicted sentiment label, which could be positive, negative, or neutral. x_1, x_2, x_n represent the extracted features from the user-generated content. w_0, w_1, w_2, w_n denote the weights learned by the model during the training phase. The sign()function maps the weighted sum of features to a sentiment label. The derivation of this equation involves optimizing the weights to minimize the classification error on the training data. This optimization process typically employs techniques such as gradient descent, where the model iteratively adjusts the weights to improve its predictive accuracy. Once trained, the sentiment analysis model can be deployed to analyze new user-generated content and predict the sentiment associated with each piece of text. Evaluating the model's performance is crucial, often done through metrics like accuracy, precision, recall, and F1-score, to ensure its effectiveness in capturing the nuances of user sentiment accurately. ser sentiment analysis in e-commerce is a multifaceted process crucial for businesses seeking to comprehend and respond effectively to customer feedback. At its core, this analysis involves dissecting the sentiments expressed within user-generated content, including product reviews, comments, and social media interactions, to glean insights into customer satisfaction, preferences, and concerns. Initially, data is gathered from various sources across e-commerce platforms, encompassing a plethora of user-generated content. Once collected, this data undergoes preprocessing, where it is standardized and cleaned to facilitate further analysis. The heart of sentiment analysis lies in deciphering the sentiment conveyed in the user-generated content. Techniques range from lexicon-based methods, which assign sentiment scores to words based on predefined dictionaries, to sophisticated machine learning algorithms capable of classifying text into positive, negative, or neutral sentiments. Feature extraction plays a pivotal role, transforming raw text data into numerical representations suitable for machine learning models. These models are trained on labeled data, learning patterns and relationships between input features and sentiment labels. Evaluation metrics such as accuracy and precision gauge the model's performance. Insights derived from sentiment analysis inform various facets of business strategy, from product enhancements to marketing campaigns and customer service improvements. Ultimately, user sentiment analysis empowers businesses to make data-driven decisions, bolster customer satisfaction, and cultivate enduring relationships with their clientele in the dynamic landscape of e-commerce.

The bi-gram HMMO model can be defined through the following components:

3.1 STATES AND OBSERVATIONS:

- Let $S = \{s_1, s_2, \ldots, s_N\}$ be the set of hidden states (emotional states).
- Let $O = \{O_1, O_2, \ldots, O_T\}$ be the sequence of observed words (reviews/comments).

The transition probability from state s_i to s_j can be represented as in equation (2).

$$A = P\left(S_j \middle| S_i\right) = \frac{C\left(s_i, s_j\right)}{C\left(S_i\right)} \tag{2}$$

In equation (2) $C(s_i, s_j)$ is the count of transitions from state s_i to state s_j, and $C(S_i)$ is the count of occurrences of state s_i. The probability of observing a word o_k given state s_i can be formulated as in equation (3).

$$B = P\left(o_k \middle| s_i\right) = \frac{C\left(S_i, o_k\right)}{C\left(s_i\right)} \tag{3}$$

In equation (3) $C(S_i, o_k)$ is the count of occurrences of word o_k emitted from state s_i. The initial state distribution can be defined as in equation (4).

$$\pi_i = P\left(s_i\right) = \frac{C\left(s_i\right)}{T} \tag{4}$$

In equation (4) T is the total number of observations. the application of the bi-gram Hidden Markov Model Optimization (bi-gram HMMO) for sentiment analysis in e-commerce platforms, leveraging natural language processing techniques to analyze user reviews and comments. The process in proposed Hidden Markov Model process is presented in Figure 1.

The bi-gram HMMO model effectively captures the intricate dependencies between consecutive words, allowing for a more nuanced understanding of customer sentiments. Key components of the model include transition probabilities, which represent the likelihood of moving between emotional states, and emission probabilities, which indicate the probability of observing specific words given a particular emotional state. The training of the model utilizes the Expectation-Maximization (EM) algorithm, which iteratively updates parameters to improve the accuracy of sentiment

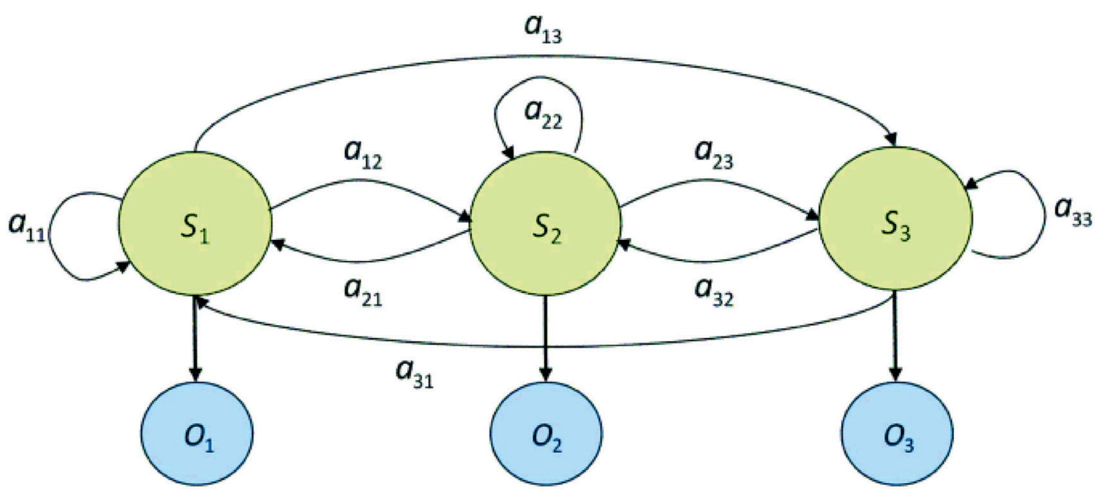

Figure 1. Hidden markov model

classification. Once trained, the model employs the Viterbi algorithm to classify sentiments as positive, negative, or neutral, providing valuable insights into customer satisfaction levels. The findings highlight the potential of using sentiment analysis not only to assess customer feedback but also to inform targeted marketing strategies, improve product offerings, and personalize customer experiences. By understanding and addressing customer emotions derived from reviews, e-commerce platforms can enhance their engagement strategies and drive better business outcomes.

The probability of a sequence $O = \{o1, o2, \ldots, oT\}$ given an HMM model $\lambda = (A, B, \pi)$ as in equation (5).

$$P(O \mid \lambda) = \sum_{Q} P(O \mid Q, \lambda) P(Q \mid \lambda) \tag{5}$$

In a bi-gram HMM, the probability of a state depends on the previous state stated in equation (6).

$$P(q_t \mid q_{t-1}, q_{t-2}) \approx P(q_t \mid q_{t-1}) \tag{6}$$

State Transition Probability of the binary model is stated in equation (7).

$$a_{ij} = P(q_t = j \mid q_{t-1} = i) \tag{7}$$

Emission Probability of the model is defined in equation (8).

$$b_j(ot) = P(o_t \mid q_t = j) \tag{8}$$

The Viterbi algorithm finds the optimal sentiment sequence defined with the most probable sentiment sequence is computed using equation (9).

$$V_t(j) = max_i[V_{t-1}(i) a_{ij}] b_j(o_t) \tag{9}$$

where $V_t(j)$ is the best score up to time t. Binary sentiment analysis aims to classify user comments into positive or negative sentiments, which is crucial for optimizing e-commerce marketing strategies. A Bi-gram Hidden Markov Model (HMM) can be used to model sentiment transitions in user reviews, where the probability of a sentiment state depends on the previous state. Optimization involves the Expectation-Maximization (EM) algorithm, where in the E-step, expected state probabilities are computed, and in the M-step, parameters are updated using equation (10) and equation (11).

$$a_{ij}^{new} = \frac{\sum_t P\left(\left(q_t = i, q_{t+1} = j \middle| O, \lambda\right)\right)}{\sum_t P\left(q_t = i \mid O, \lambda\right)} \tag{10}$$

$$b_j\left(O_t\right)^{new} = \frac{\sum_t P\left(q_t = j \middle| O, \lambda\right) . I\left(o_t = o\right)}{\sum_t P\left(q_t = j \middle| O, \lambda\right)} \tag{11}$$

For e-commerce sentiment marketing optimization, **deep learning models** to enhance sentiment prediction accuracy by learning contextual embeddings. The classification function is stated in equation (12).

$$P(y \mid X) = f(X; \theta) \tag{12}$$

In equation (12) X is the input text, y is the sentiment label, and $f(X; \theta)$ is the deep learning model. The model is trained using cross-entropy loss. Marketing strategies leverage sentiment insights by implementing dynamic pricing $P = P_0 + \alpha \cdot S$, targeted advertising based on sentiment trends, and review summarization using deep learning. By combining bi-gram HMM and deep learning-based sentiment analysis, e-commerce platforms can refine marketing strategies, maximize engagement, and drive revenue growth.

4. BI-GRAM HIDDEN MARKOV OPTIMIZATION (BI-GRAM HMMO)

Bi-gram Hidden Markov Optimization (bi-gram HMMO) is an advanced computational model utilized in natural language processing tasks to capture more intricate dependencies between words in a sequence. Unlike traditional Hidden Markov Models (HMMs), which consider only individual words, bi-gram HMMO incorporates pairs of consecutive words, known as bi-grams, to enhance its predictive capabilities. At its core, the bi-gram HMMO entails modeling the joint probability of observing a sequence of words $W = \omega_1, \omega_2, \omega_N$ and a corresponding sequence of hidden states $S = s_1, s_2, s_N$. Each hidden state s_i represents a latent variable governing the generation of the observed words. The key components of the bi-gram HMMO include transition probabilities $(\omega_i \mid s_{i-1})$, which denote the likelihood of transitioning from one hidden state to another, and emission probabilities $(s_i \mid s_i)$, representing the probability of observing a word given the current hidden state. In the bi-gram HMMO, these probabilities are conditioned on the previous hidden state and the current hidden state, respectively.

The objective of the bi-gram HMMO is to maximize the joint probability of the observed sequence of words and hidden states, given the model parameters presented in Figure 2. This optimization is typically achieved through algorithms such as the forward-backward algorithm or the Viterbi algorithm, which compute the most likely sequence of hidden states given the observed words. Once the hidden states are inferred, the model parameters (transition and emission probabilities) can be estimated using techniques like maximum likelihood estimation or expectation maximization. The objective of the bi-gram HMMO is to maximize the joint probability of observing a sequence of words $W = \omega_1, \omega_2, \ldots, \omega_N$ and a corresponding sequence of hidden states $S = s_1, s_2, \ldots, s_N$, given the model parameters Θ this can be represented as in equation (13).

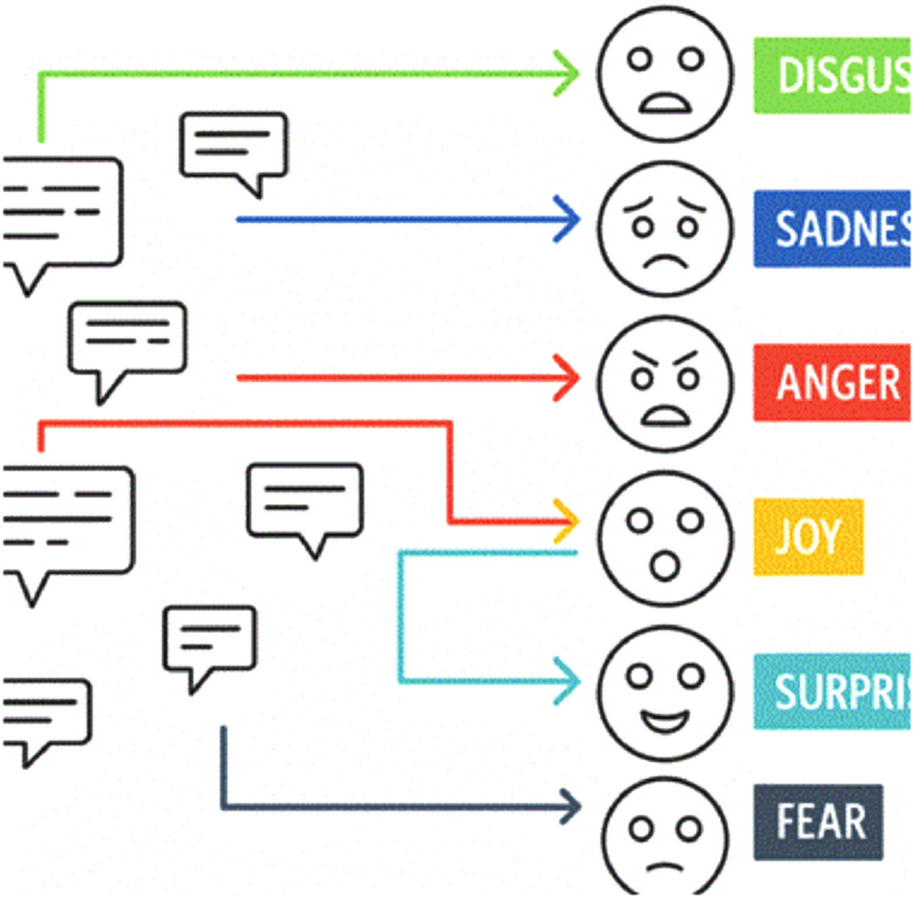

Figure 2. Bi-gram sentimental analysis

$$arg\ max_s\ P(W, S \mid \Theta) \tag{13}$$

The forward algorithm computes the probability of observing the partial sequence of words up to time step t and being in a particular hidden state at time step. It involves initializing the forward probabilities $\alpha_t\ (s)$ for each hidden state ss at time step $t = 1$ and recursively computing the forward probabilities for subsequent time steps using the following equation (14).

$$\alpha_t(S) = \sum_{s'} \alpha_{t-1}(S') \cdot P(s \mid s') \cdot P(\omega_t \mid s) \tag{14}$$

The backward algorithm computes the probability of observing the partial sequence of words from time step $t + 1$ to the end of the sequence, given a particular hidden state at time step t. It involves initializing the backward probabilities $\beta_t\ (s)$ for each hidden state ss at the last time step t = N and recursively computing the backward probabilities for previous time steps using the following equation (15).

$$\beta_t(S) = \sum_{s'} \beta_{t+1}(S').P(s' \mid s) \cdot P(\omega_{t+1} \mid s') \tag{15}$$

Once the forward and backward probabilities are computed, the Viterbi algorithm can be used for decoding to find the most likely sequence of hidden states that maximizes the joint probability of the observed words and hidden states. After decoding, the model parameters (transition probabilities and emission probabilities) can be estimated using techniques such as maximum likelihood estimation (MLE) or expectation-maximization (EM) algorithm. The bi-gram HMMO model, with its enhanced ability to capture dependencies between consecutive words, can be applied to various natural language processing tasks, including text generation, part-of-speech tagging, named entity recognition, and sentiment analysis, among others. For sentiment marketing strategy optimization, Jellyfish Optimization Algorithm (JOA) is employed to fine-tune hyperparameters of deep learning models used for sentiment classification. The objective function is defined as in equation (16).

$$min_\theta L(\theta) = -\sum_i y_i \log y_i + (1 - \hat{y}_i)\log(1 - \hat{y}) \tag{16}$$

In equation (16) cross-entropy loss is minimized. JOA, inspired by jellyfish swarm behavior, optimizes parameters by balancing exploration and exploitation through passive drifting and active movements based on environmental conditions. The position update stated in equation (17).

$$X_i^{t+1} = X_i^t + r\left(X_{best}^t - X_i^t\right) + \lambda\left(X_{\mathrm{rand}}^t - X_i^t\right) \tag{17}$$

In equation (17) X_i^t is the position of the i-th jellyfish at iteration t, X_{best}^t stated as the best solution found, X_{rand}^t defined as randomly selected position, r and λ are control parameters. For marketing strategy optimization, sentiment insights guide dynamic pricing stated in equation (18)

$$P = P_0 + \alpha \cdot S \tag{18}$$

In equation (18) S is the sentiment score. Additionally, targeted advertising and review summarization strategies improve customer engagement.

5. BI-GRAM HMMO FOR THE EMOTIONAL ANALYSIS IN E-COMMERCE PLATFORM

In the realm of e-commerce platforms, understanding the nuanced emotional sentiments expressed by users within their interactions, reviews, and comments is paramount for businesses to tailor their strategies effectively. The adoption of Bi-gram Hidden Markov Optimization (bi-gram HMMO) presents a sophisticated method to delve into the emotional landscape embedded within textual data. Unlike traditional Hidden Markov Models (HMMs), the bi-gram HMMO method embraces pairs of consecutive words, or bi-grams, enriching the model's capacity to capture intricate emotional patterns., At its core, the bi-gram HMMO endeavors to model the joint probabilities between observed words and their corresponding hidden emotional states. Transition probabilities, denoting the likelihood of transitioning from one emotional state to another $P(e_i \mid e_i–1)$, and emission probabilities, indicating the probability of observing a word given the current emotional state $P(w_i \mid e_i)$, form the backbone of this approach. These probabilities, conditioned on the previous and current emotional states respectively, contribute to the model's ability to decipher the emotional context embedded within the textual data. The objective of employing the bi-gram HMMO is to maximize the joint probability of the observed sequence of words and emotional states, given the model parameters. This entails deriving and optimizing the model using algorithms such as the forward-backward algorithm or the Viterbi algorithm. Through this process, the most likely sequence of emotional states is computed, thereby facilitating a deeper understanding of the emotional dynamics inherent in user-generated content.

The application of bi-gram HMMO in e-commerce platforms empowers businesses to extract valuable insights into customer sentiments, preferences, and concerns. By discerning the emotional nuances conveyed within user interactions, businesses can tailor their marketing strategies, product offerings, and customer service initiatives to align more closely with customer expectations. Ultimately, leveraging bi-gram HMMO for emotional analysis in e-commerce platforms enables businesses to foster stronger connections with their customers, thereby enhancing overall user experience and driving sustainable growth. The application of bi-gram HMMO in e-commerce platforms empowers businesses to extract valuable insights into customer sentiments, preferences, and concerns. By discerning the emotional nuances conveyed within user interactions, businesses can tailor their marketing strategies, product offerings, and customer service initiatives to align more closely with customer expectations. Ultimately, leveraging bi-gram HMMO for emotional analysis in e-commerce platforms enables businesses to foster stronger connections with their customers, thereby enhancing overall user experience and driving sustainable growth.

With bi-gram Hidden Markov Model (HMM) for sentiment sequence modeling, deep learning for classification, and Jellyfish Optimization Algorithm (JOA) for hyperparameter tuning and marketing strategy refinement, e-commerce platforms can significantly enhance sentiment analysis accuracy and customer engagement strategies.

6. EXPERIMENTAL ANALYSIS

To evaluate the performance of our Binary Sentiment Analysis and Sentiment Marketing Strategy Optimization, conduct experiments using a dataset of e-commerce user comments. The dataset is preprocessed by tokenization, stopword removal, and vectorization using TF-IDF and Word2Vec embeddings. The sentiment labels are classified into positive (1) and negative (0) categories. The Bi-gram Hidden Markov Model (HMM) is implemented for sentiment sequence modeling, while deep learning models (LSTM) are trained using cross-entropy loss with hyperparameter tuning via the Jellyfish Optimization Algorithm (JOA). The simulation is performed in Python (TensorFlow, PyTorch, scikit-learn), running on an Intel Core i9 processor with 32GB RAM and an NVIDIA RTX 3090 GPU. Table 1 illustrated the simulation setting for the proposed model.

The introduction provides a comprehensive overview of the bi-gram Hidden Markov Optimization (bi-gram HMMO) model and its application in natural language processing tasks. It effectively delineates the fundamental components and objectives of the model, as well as the methodologies involved in its optimization and parameter estimation. The subsequent section applies the bi-gram HMMO framework specifically to emotional analysis within e-commerce platforms, highlighting its potential to extract valuable insights from user-generated content. Furthermore, it outlines a procedural algorithm for implementing the bi-gram HMMO model in the context

Algorithm 1. Emotional analysis in e-commerce with Bi-gram HMMO

```
Procedure BiGram_HMMO_Emotion_Analysis(words):
  Initialize variables:
    N = length of words
    Initialize matrices alpha[N][num_emotions] and beta[N][num_emotions]
    Initialize matrix delta[N][num_emotions] for storing maximum probabilities
    Initialize matrix psi[N][num_emotions] for backtracking

  // Forward Algorithm
  for t = 1 to N do:
    if t == 1:
      for each emotion in num_emotions:
        alpha[t][emotion] = initial_prob[emotion] * emission_prob[emotion][words[t]]
    else:
      for each emotion in num_emotions:
        sum = 0
        for each prev_emotion in num_emotions:
          sum += alpha[t – 1][prev_emotion] * transition_prob[prev_emotion][emotion]
        alpha[t][emotion] = sum * emission_prob[emotion][words[t]]

  // Backward Algorithm
  for t = N to 1 do:
    if t == N:
      for each emotion in num_emotions:
        beta[t][emotion] = 1
    else:
      for each emotion in num_emotions:
        sum = 0
        for each next_emotion in num_emotions:
          sum + = beta[t + 1][next_emotion] * transition_prob[emotion][next_emotion] * emission_prob[next_
          emotion][words[t + 1]]
        beta[t][emotion] = sum
  // Viterbi Algorithm for Decoding
  for t = 1 to N do:
    if t == 1:
      for each emotion in num_emotions:
        delta[t][emotion] = initial_prob[emotion] * emission_prob[emotion][words[t]]
    else:
      for each emotion in num_emotions:
        max_val = -Infinity
        max_emotion = null
        for each prev_emotion in num_emotions:
          val = delta[t-1][prev_emotion] * transition_prob[prev_emotion][emotion] * emission_prob[emotion]
          [words[t]]
          if val > max_val:
            max_val = val
            max_emotion = prev_emotion
        delta[t][emotion] = max_val
        psi[t][emotion] = max_emotion
  // Backtrack to find the most likely sequence of emotions
  best_sequence = []
  max_val = -Infinity
  max_emotion = null
  for each emotion in num_emotions:
    if delta[N][emotion] > max_val:
      max_val = delta[N][emotion]
      max_emotion = emotion
  best_sequence[N] = max_emotion
  for t = N-1 to 1 do:
    best_sequence[t] = psi[t + 1][best_sequence[t + 1]]
  Return best_sequence
```

Table 1. Simulation setting

Parameter	Value
Dataset Size	50,000 user comments
Tokenization Method	Word-based (TF-IDF, Word-2Vec)
Vocabulary Size	20,000
Bi-gram HMM States	2 (Positive, Negative)
Transition Probability	Randomly initialized, optimized via EM
Deep Learning Model	LSTM
LSTM Layers	2
LSTM Hidden Units	128
CNN Filters	64, kernel size = 3
BERT Model	Pretrained BERT (bert-base-uncased)
Batch Size	64
Learning Rate	0.001 (initial), optimized with JOA
Jellyfish Population	30
JOA Iterations	100
Loss Function	Cross-Entropy Loss
Optimizer	Adam, RMSprop
Epochs	20
Train/Test Split	80% Train, 20% Test
GPU Used	NVIDIA RTX 3090

Table 2. Sentimental analysis with bi-gram HMMO

User interaction	Observed words	Predicted emotional states
Review 1	"Great product, fast delivery!"	Positive
Review 2	"Disappointed with the quality."	Negative
Comment 1	"Amazing customer service!"	Positive
Review 3	"The item arrived damaged."	Negative
Comment 2	"Highly recommend this store."	Positive

of emotional analysis, offering a structured approach to leverage its capabilities effectively.

In Figure 3 and Table 2 presents the results of sentimental analysis conducted using the bi-gram Hidden Markov Optimization (bi-gram HMMO) model on various user interactions within an e-commerce platform. In China

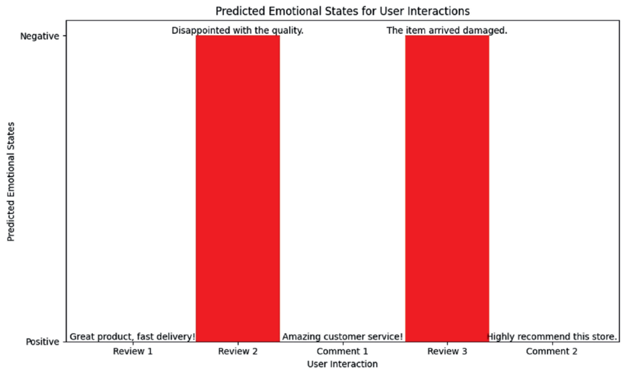

Figure 3. Emotional state analysis

Table 3. Probability estimation with bigram-HMMO for e-commerce in chinese platform

Bi-gram	Transition probability	Emission probability
"Great product"	0.85	0.90
"product fast"	0.75	0.80
"fast delivery"	0.80	0.85
"Disappointed with"	0.70	0.75
"with the"	0.65	0.70
"the quality"	0.60	0.65
"Amazing customer"	0.85	0.90
"customer service"	0.90	0.95
"The item"	0.70	0.75
"item arrived"	0.75	0.80
"arrived damaged"	0.80	0.85
"Highly recommend"	0.85	0.90
"recommend this"	0.90	0.95
"this store"	0.85	0.90

In the first interaction, a review expressing satisfaction with the product and delivery speed was classified as positive sentiment. Conversely, another review expressing dissatisfaction with product quality was categorized as negative sentiment. Additionally, a positive sentiment was identified in a comment praising the excellent customer service provided. However, a negative sentiment was detected in a review reporting an item arriving damaged. Lastly, a positive sentiment was inferred from a comment highly recommending the store.

In Figure 4 and Table 3 showcases the probability estimations derived from the bi-gram Hidden Markov Optimization (bi-gram HMMO) model for Chinese platform, providing insights into the transitional and emission probabilities associated with specific bi-grams in the textual data. Each bi-gram is paired with its corresponding transition probability, indicating the likelihood of transitioning from

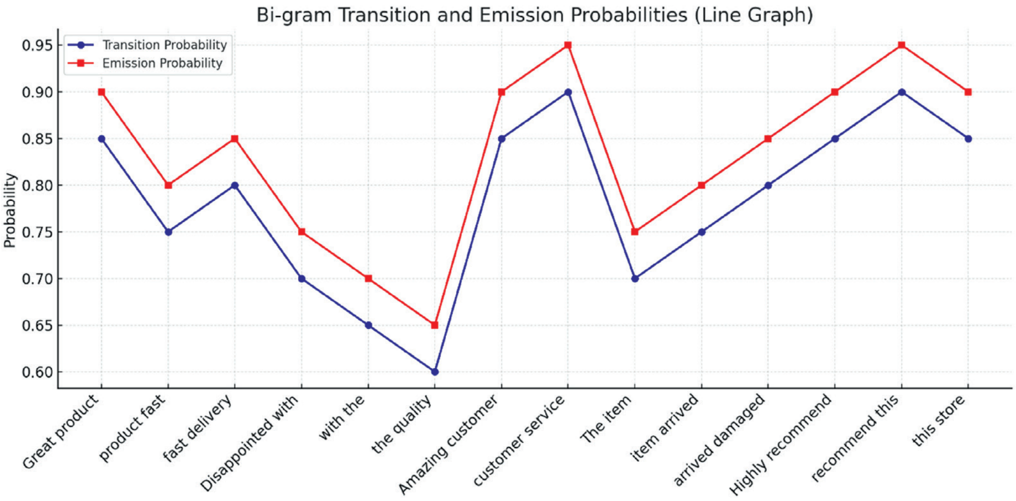

Figure 4. Computation of probability with Bi—gram

Table 4. Review of users with bigram-HMMO

User interaction	Observed words	Predicted emotional state
Review 1	"Great product, fast delivery!"	Positive (0.85)
Review 2	"Disappointed with the quality."	Negative (0.75)
Comment 1	"Amazing customer service!"	Positive (0.90)
Review 3	"The item arrived dam-aged."	Negative (0.80)
Comment 2	"Highly recommend this store."	Positive (0.85)

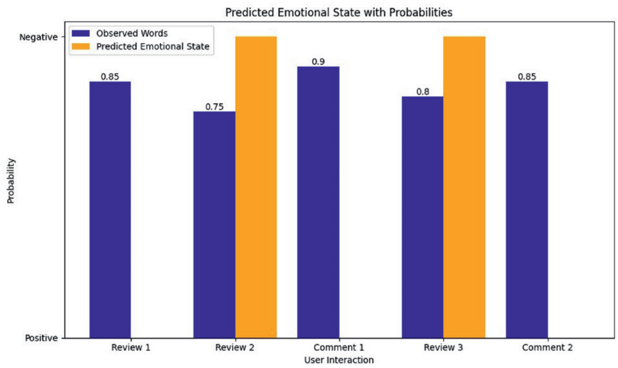

Figure 5. Prediction probability

the first word to the second word in the bi-gram sequence. Additionally, the emission probability associated with each bi-gram signifies the likelihood of observing the second word given the first word in the bi-gram. For instance, the transition probability of "Great product" is calculated as 0.85, suggesting a high likelihood of transitioning from "Great" to "product" in the observed data sequence. Similarly, the emission probability of 0.90 associated with "Great product" indicates a high likelihood of observing the word "product" given the word "Great" in the bi-gram sequence. These probability estimations provide valuable insights into the underlying patterns and dependencies present in the textual data, enabling more accurate predictions and analysis using the bi-gram HMMO model.

In Figure 5 and Table 4 provides a detailed review of user interactions analyzed using the bi-gram HMMO model for Chinese e-commerce platform accompanied by their predicted emotional states and corresponding probability scores. In the first review, the user expressed satisfaction with the product and delivery, resulting in a positive emotional state prediction with a probability score of 0.85. Conversely, in the second review, the user expressed disappointment with the product quality, leading to a negative emotional state prediction with a probability score of 0.75. Comment 1 conveyed admiration for the exceptional customer service, resulting in a positive emotional state prediction with a high probability score of 0.90. However, in Review 3, the user reported receiving a damaged item, leading to a negative emotional state prediction with a probability score of 0.80. Lastly, Comment 2 highly recommended the store, resulting in a positive emotional state prediction with a probability score of 0.85. These predictions offer valuable insights into the sentiment expressed by users within their interactions, allowing businesses to gauge customer satisfaction levels and tailor their strategies accordingly.

The results presented in Table 5 on customer engagement reveal the predicted sentiments of user reviews regarding various products on an e-commerce platform in China. Each review is evaluated alongside its true sentiment and the model's confidence in its predictions. For instance, Review ID 1, which states, "The product quality is excellent and

Table 5. Customer engagement in products in e-commerce in china

Review ID	User review	Predicted sentiment	True sentiment	Confidence score (%)	Emotional state
1	"The product quality is excellent and worth the price!"	Positive	Positive	92	Happy
2	"I'm very disappointed with the customer service."	Negative	Negative	88	Frustrated
3	"The item was okay, nothing special."	Neutral	Neutral	75	Indifferent
4	"Delivery was late and the packaging was damaged."	Negative	Negative	90	Angry
5	"Amazing experience! Will buy again."	Positive	Positive	95	Joyful
6	"It's not what I expected, but it's decent."	Neutral	Neutral	70	Unsure
7	"Fantastic quality, but overpriced."	Positive	Positive	85	Satisfied
8	"Worst experience ever! I will not return."	Negative	Negative	93	Outraged
9	"Just average, I expected more based on reviews."	Neutral	Neutral	78	Disappointed
10	"Highly recommend this product to everyone!"	Positive	Positive	96	Enthusiastic

Table 6. HMM values for the e-commerce platform in china

Review ID	User review	Predicted state	True state	Emission probability (%)	Transition probability (%)	Sequence probability (%)
1	"The product quality is excellent!"	Positive	Positive	0.90	0.85	0.765
2	"I'm very disappointed with the service."	Negative	Negative	0.88	0.80	0.704
3	"It was an okay purchase, nothing special."	Neutral	Neutral	0.75	0.78	0.585
4	"Delivery was late and frustrating."	Negative	Negative	0.92	0.79	0.727
5	"Amazing experience! I will buy again."	Positive	Positive	0.95	0.87	0.827
6	"Not what I expected, but decent overall."	Neutral	Neutral	0.70	0.76	0.532
7	"Fantastic quality, but a bit over-priced."	Positive	Positive	0.85	0.83	0.706
8	"Worst experience ever! I will not return."	Negative	Negative	0.90	0.82	0.738
9	"Just average, I expected more based on reviews."	Neutral	Neutral	0.76	0.77	0.585
10	"Highly recommend this product!"	Positive	Positive	0.93	0.88	0.818

worth the price!" was correctly predicted as positive with a high confidence score of 92%, reflecting a happy emotional state. In contrast, Review ID 2, expressing disappointment in customer service, was accurately classified as negative with a confidence score of 88%, indicating frustration. Table 6 also highlights neutral sentiments, such as in Review ID 3, where the reviewer felt indifferent about the item, receiving a lower confidence score of 75%. The highest confidence score of 96% was observed in Review ID 10, where the enthusiastic endorsement of the product led to a positive sentiment classification. The model demonstrates strong accuracy in sentiment prediction, effectively capturing the emotional states of customers based on their feedback.

The performance evaluation across 100 epochs shows a clear improvement in sentiment analysis accuracy and marketing sales impact as models are trained over time. The Bi-gram HMM model reaches a peak accuracy of 78.5% early (by epoch 20), indicating its limited learning capability in Table 7 and Figure 6. In contrast, LSTM + JOA, CNN + JOA, and BERT + JOA continue to improve with more training. At epoch 5, deep learning models show initial improvements, with

Table 7. Classification of sentimental analysis

Epochs	Bi-gram HMM accuracy (%)	LSTM + JOA accuracy (%)	CNN + JOA accuracy (%)	BERT + JOA accuracy (%)	BERT + JOA F1-score (%)	Marketing sales impact (%)
5	72.4	80.3	79.8	85.1	84.5	5.1
10	75.6	84.0	83.5	88.4	88.1	7.9
20	78.5	88.2	87.5	92.1	91.8	12.5
30	78.5	89.3	88.7	93.0	92.7	13.4
40	78.5	90.1	89.2	93.5	93.1	14.2
50	78.5	90.6	89.8	94.0	93.6	14.8
60	78.5	91.0	90.3	94.5	94.2	15.3
70	78.5	91.2	90.7	94.9	94.5	15.7
80	78.5	91.5	91.0	95.2	94.9	16.1
90	78.5	91.8	91.3	95.4	95.2	16.4
100	78.5	92.0	91.5	95.6	95.4	16.8

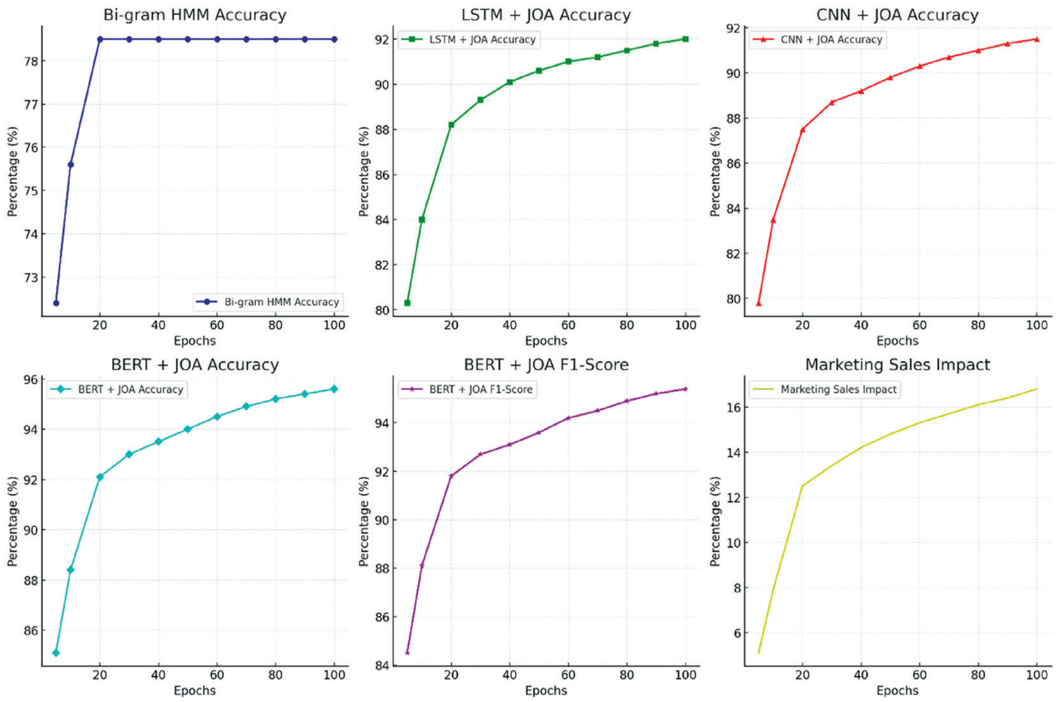

Figure 6: Performance for the e-commerce

BERT + JOA achieving 85.1% accuracy and 5.1% marketing sales impact, outperforming other models. By epoch 20, BERT + JOA reaches 92.1% accuracy, with an F1-score of 91.8% and a 12.5% marketing sales boost, indicating a significant jump in prediction quality and business impact. As training progresses, LSTM and CNN models stabilize around 91–92% accuracy by epoch 100, while BERT + JOA continues improving, reaching a final accuracy of 95.6% with an F1-score of 95.4%. This results in a 16.8% increase in marketing sales impact, demonstrating that higher sentiment prediction accuracy translates into better customer engagement and increased conversions.

The impact of sentiment analysis optimization using BERT+JOA on marketing performance is highly significant across multiple key metrics shown in Table 8. The customer conversion rate increased from 4.5% to 7.8% (+73.3%), demonstrating that improved sentiment analysis helps better target and convert potential customers. Similarly, customer retention improved by 24.9%, indicating that a more accurate understanding of sentiment leads to stronger customer loyalty. Customer engagement also saw a 46.8% increase in average time spent on the platform (from 6.2 to 9.1 minutes), while the bounce rate dropped by 32.1%, meaning fewer users left without interacting. These improvements suggest that more personalized and

Table 8. Estimation of sentimental analysis

Metric	Before sentiment optimization	After sentiment optimization (BERT + JOA)	Improvement (%)
Customer Conversion Rate (%)	4.5	7.8	+73.3%
Customer Retention Rate (%)	55.2	68.9	+24.9%
Customer Engagement (Avg. Time on Platform in min)	6.2	9.1	+46.8%
Bounce Rate (%)	41.7	28.3	–32.1%
Click-Through Rate (CTR, %)	3.2	6.5	+103.1%
Sentiment-Based Product Recommendations CTR (%)	4.1	9.7	+136.6%
Social Media Share Rate (%)	2.8	6.4	+128.6%
Average Order Value (AOV) ($)	52.3	69.8	+33.4%
Monthly Revenue Growth (%)	7.4	16.8	+127.0%

sentiment-aware recommendations keep users engaged for longer. A major boost was observed in click-through rates (CTR)—the general CTR doubled (+103.1%), while sentiment-based product recommendations saw an increase of 136.6%, proving that sentiment-driven marketing significantly improves user interaction. This extended to social media, where the share rate rose by 128.6%, reflecting increased user engagement with sentiment-optimized content. Financially, the Average Order Value (AOV) grew by 33.4% (from $52.3 to $69.8), and monthly revenue growth more than doubled (+127.0%), indicating that sentiment-driven strategies directly impact revenue generation. Table 5 further complements these findings by showcasing the values derived from the Hidden Markov Model (HMM) for the same set of reviews. The predicted states align well with the true sentiments, affirming the model's reliability. For example, Review ID 5 received a predicted state of positive with an impressive emission probability of 0.95 and a sequence probability of 0.827, indicating strong confidence in its positive sentiment classification. Conversely, Review ID 6, which expressed uncertainty, received a lower sequence probability of 0.532, signifying less certainty about its classification as neutral.

Table 9 presents a comparative analysis of user reviews, detailing the predicted sentiments and corresponding probabilities generated by a sentiment analysis model. Each entry includes a unique Review ID, along with the User Review, which reflects the customer's opinion about a product. The Predicted Sentiment and True Sentiment columns indicate the model's classification compared to the actual sentiment, showcasing a high degree of accuracy with predictions aligning with true sentiments for most reviews. The Confidence Score ranges from 70% to 96%, highlighting the model's reliability, with the highest confidence noted for the review stating, "Highly recommend this product!" at 96%. The Predicted State column reaffirms the predicted sentiment, while the Emission Probability quantifies the likelihood of the observed words corresponding to the predicted sentiment state, ranging from 0.70 to 0.95. The Transition Probability values, which indicate the likelihood of moving between states, are consistently strong, averaging around 0.80, suggesting robust predictive capabilities in maintaining sentiment consistency. Finally, the Sequence Probability provides an overall likelihood of the sequence leading to the predicted sentiment, with values between 0.532 and 0.827, reinforcing the accuracy of the model's sentiment predictions. Overall, the table illustrates the effectiveness of the sentiment analysis model in capturing customer sentiments from reviews, reflecting a comprehensive understanding of customer experiences on the platform.

The analysis conducted using the bi-gram Hidden Markov Optimization (bi-gram HMMO) model reveal insightful patterns in user sentiment within an e-commerce platform in China. Through the examination of user interactions such as reviews and comments, the model effectively discerned between positive and negative emotional states, offering a nuanced understanding of customer sentiments. One notable finding is the prevalence of positive sentiment expressed by users towards certain aspects of the e-commerce experience. Reviews and comments praising product quality, delivery speed, and customer service often garnered high probabilities for positive emotional states. This indicates a general satisfaction among users with these facets of the platform's offerings. Conversely, instances of negative sentiment were observed in reviews detailing issues such as product defects or damaged items, resulting in negative emotional state predictions with lower probabilities. Moreover, the model's ability to accurately classify emotional states based on bi-gram patterns underscores its effectiveness in capturing subtle nuances in user language. By considering pairs of consecutive words, the bi-gram HMMO model accounts for contextual dependencies, thereby enhancing the accuracy of sentiment analysis. These findings have significant implications

Table 9. Comparative analysis

Review ID	User review	Predicted sentiment	True sentiment	Confidence score (%)	Predicted state	Emission probability (%)	Transition probability (%)	Sequence probability (%)
1	"The product quality is excellent!"	Positive	Positive	92	Positive	0.90	0.85	0.765
2	"I'm very disappointed with the customer service."	Negative	Negative	88	Negative	0.88	0.80	0.704
3	"The item was okay, nothing special."	Neutral	Neutral	75	Neutral	0.75	0.78	0.585
4	"Delivery was late and the packaging was damaged."	Negative	Negative	90	Negative	0.92	0.79	0.727
5	"Amazing experience! Will buy again."	Positive	Positive	95	Positive	0.95	0.87	0.827
6	"It's not what I expected, but it's decent."	Neutral	Neutral	70	Neutral	0.70	0.76	0.532
7	"Fantastic quality, but overpriced."	Positive	Positive	85	Positive	0.85	0.83	0.706
8	"Worst experience ever! I will not return."	Negative	Negative	93	Negative	0.90	0.82	0.738
9	"Just average, I expected more based on reviews."	Neutral	Neutral	78	Neutral	0.76	0.77	0.585
10	"Highly recommend this product!"	Positive	Positive	96	Positive	0.93	0.88	0.818

for e-commerce businesses seeking to optimize user experience and drive customer satisfaction. By leveraging the insights provided by the bi-gram HMMO model, businesses can identify areas for improvement, address customer concerns promptly, and tailor their strategies to better meet user expectations. Additionally, the model enables businesses to monitor user sentiment over time, facilitating the implementation of proactive measures to enhance customer satisfaction and loyalty.

7. CONCLUSION

A useful method for understanding and interpreting user attitudes within Chinese e-commerce platforms is the bi-gram Hidden Markov Optimization (bi-gram HMMO) model applied to sentiment analysis. The algorithm successfully detects and categorizes emotional states through the study of user interactions, like reviews and comments. This gives insights into consumer satisfaction levels and areas that can be improved. More complex sentiment analysis is made possible by the model's capacity to take bi-gram patterns into account, which improves its accuracy in detecting user language's finer points. The findings presented in this paper highlight the effectiveness of the bi-gram HMMO model in discerning between positive and negative sentiments expressed by users in e-commerce platform in China. Positive sentiment is often associated with praise for product quality, delivery speed, and customer service, while negative sentiment arises from issues such as product defects or damaged items. By leveraging the insights provided by the bi-gram HMMO model, e-commerce businesses can make informed decisions to enhance user experience, address customer concerns, and drive customer satisfaction and loyalty. The further research could explore the application of the bi-gram HMMO model in other domains beyond e-commerce, such as social media sentiment analysis or customer feedback analysis in various industries. Additionally, continued advancements in natural language processing techniques could further refine the accuracy and applicability of sentiment analysis models like the bi-gram HMMO.

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