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SENTIMENT ANALYSIS MODEL  
USING EXTENDED SCALE FOR  
POLARITY DETECTION**

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# CUTTING-EDGE CHATBOT SENTIMENT ANALYSIS MODEL USING EXTENDED SCALE FOR POLARITY DETECTION

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**ABSTRACT:** Chatbots can comprehend human moods and emotions thanks to sentiment analysis. People are emotional beings. When your consumers engage with a chatbot for customer support, they anticipate that the bot will be able to discern their emotions, tone, and mood and respond accordingly. Assessing consumers' interactions with chatbots is one of the fascinating domains in which sentiment analysis finds use. AI chatbots have been developed for customer support in an effort to improve customer service and lower corporate costs. Chatbot sentiment analysis is the process of identifying a user's words and voice when they interact with a chatbot, regardless of their emotional state—happy, sad, afraid, or angry. Customers aren't guaranteed to forget or disregard a negative encounter just because they dealt with a chatbot. This clearly indicates the importance of carrying out chatbot sentiment analysis in order to better understand the emotions of customers and thereby offer a tailored response. The intricacies of conducting sentiment analysis on chatbots are covered in this study. It outlines the process for conducting sentiment analysis on chatbots and demonstrates how to automatically identify sentiment in talks between chatbots and customers. Furthermore, the suggested approach investigates the analysis and classification of text sentiment as well as the use of chatbot sentiment analysis by businesses to automatically categorize customer comments as positive, negative, or neutral, helping them to accurately grasp consumer sentiment. The proposed work employs the extended sentiment scale (nonary scale) developed in ERBA-DSL model of our previous work to detect the polarity of the sentiment in chatbot-customer interaction and achieves a reasonably good F1-score of 84%.

**KEYWORDS:** Chatbot Sentiment Analysis, Chatbot-Customer Interaction, Sentiment-Aware Chatbot Response Generation.

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## 1. INTRODUCTION

Digital methods of communication are now essential for businesses to engage with their clientele. Numerous businesses use live chat interfaces to provide online services, allowing clients to communicate with customer support agents directly. For many young people, text-based service interactions are the most convenient and economical method of contact. Chatbots are one piece of technology that's frequently used to help customer support representatives during online service interactions. Chatbots are software-driven systems that are used in a variety of businesses and are intended to communicate with people through text-based natural language. Sentiment analysis for chatbots assesses how your consumers engage with your chatbot. In order to ascertain whether a consumer is happy, sad, fearful, or furious, you must analyse the tone and language they use when communicating with your chatbot. You can pinpoint areas in which you need to improve based on these

encounters. A sentiment, whether positive or negative, is an emotion conveyed through writing. Through customer service or other touchpoints where you or the team must engage with customers, sentiment analysis in customer service enables you to get feedback on a customer's experience based on the conversations you have with them.

These days, chatbots are commonplace. The latest generation of AI chatbots, sometimes referred to as "virtual agents" or "intelligent virtual assistants," can comprehend natural language conversations using sophisticated language models and automate relevant actions. [3] There have been various attempts to simulate human conduct in computer agents since the dawn of computing. ELIZA was the first chatbot in history to simulate a psychologist's behaviour. [7] Online services are paying a lot of attention to chatbots, which are software-based entities designed to converse with users in natural language. The difficulty lies in determining the best methods for gauging the level of consumer satisfaction with chatbots. It is possible to pre-train chatbots to comprehend client enquiries and provide relevant answers [8].

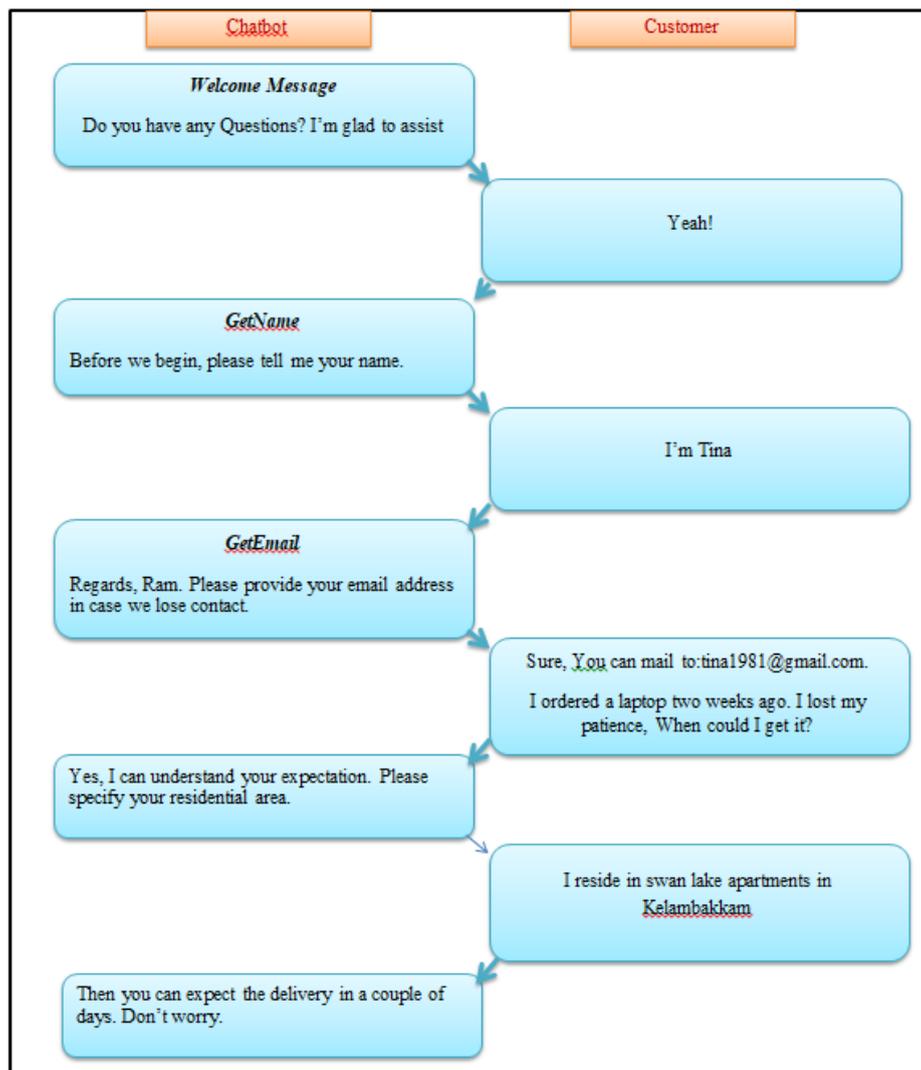
## 2. LITERATURE SURVEY

[6] The contributors have conducted experiments pertaining to the fluctuations in consumer attitudes within the retail services sector. They have suggested an automated hybrid sentiment analysis method. It turns out that people's perceptions of chatbots are generally less negative than those about human agents. [7] The difficulty of gauging chatbots' level of client happiness was tackled by the suggested approach. The purpose of this research is to determine whether automated sentiment analysis techniques can be used to gauge consumer pleasure. The association between objectivity ratings and subjective customer satisfaction values was investigated after a comparison of several sentiment analysis techniques. Lastly, if this reliance is true for every sequence in the dialogue, it is verified.

[3] To enhance chatbot responses, the authors of this research have suggested a framework for creating chatbots. Timelines and sentiment analysis are two features of the suggested architecture that help provide better answers. [4]The authors have suggested creating a personalized chatbot that uses sentiment analysis methods to respond to each user in a unique way. [5] The employment of conversational agents to assist people with mental diseases is the topic of this study. This is an important issue that, if left unchecked, could lead to serious issues.

## 3. METHODOLOGY

The scenario depicted in Figure 3.1 represents a typical chatbot-customer interaction that takes place in e-commerce websites. A typical chatbot initially welcomes the customer on a happy note, followed by lead generation process which involves collecting the customer's personal information such as name, address and email ID. Subsequently, the customer posts his/her queries which are answered by the chatbot.



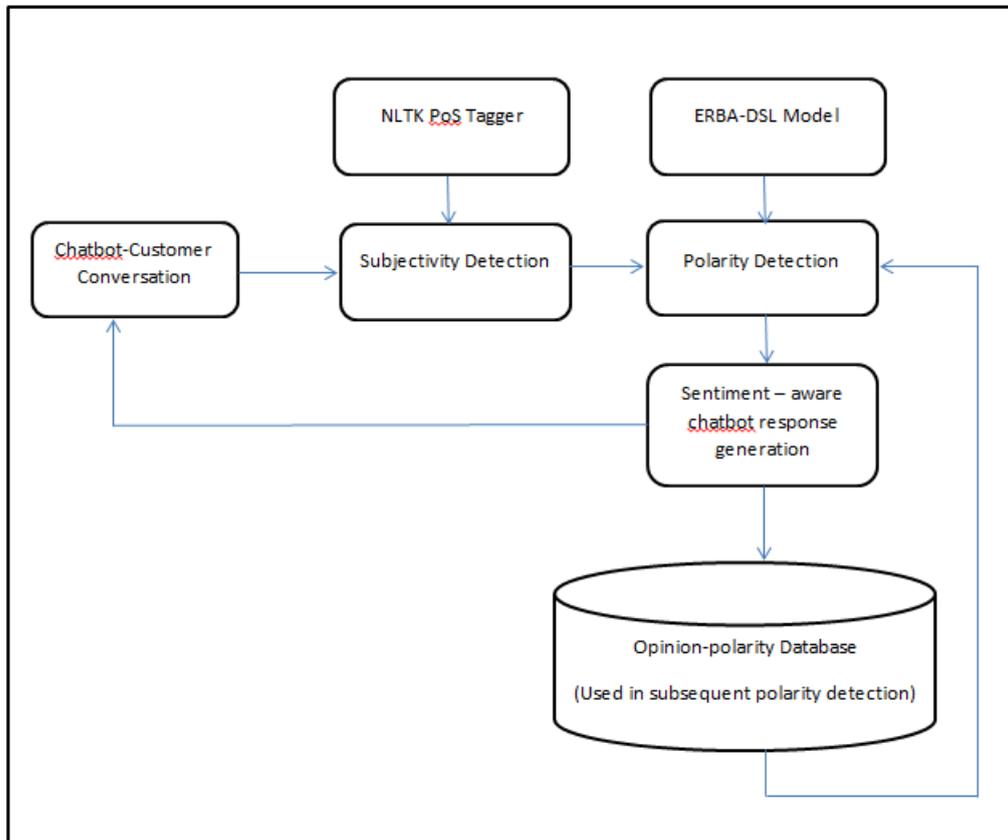
**Figure 3.1 Workflow of Chatbot-Customer Interaction**

The proposed framework carries out chatbot sentiment analysis in two phases, namely, Subjectivity detection and polarity detection. Prior to the first phase, pre-processing tasks are carried out in order to make the text ready for analysis. The pre-processing tasks include tokenization, stop-word removal and stemming. In the tokenization process, the text to be analysed is converted to individual units/words. Following the tokenization process, stop words that do not make any meaningful contribution to the analysis task are removed from the text. Subsequently, stemming is carried out in order to bring the appropriate words to their root form. As an example of stemming, consider the words, “knocking”, “knocked”, “knock”, the root form of all these three words is “knock”.

The proposed system architecture is shown in Figure 3.2. In the first phase, subjectivity detection, the text is analysed for the presence of any subjective content that carry sentiments expressed by the client. To carry out this task, PoS tagging concept is applied. A PoS tagger labels every word in the given sentence with its appropriate parts of speech tag such as VB for verb, JJ for adjective and so on. If a sentence contains a noun and an adjective, it is supposed to contain subjective information possessing some sentiment over an aspect. Therefore, those sentences that have a noun and an adjective are filtered as subjective sentences and are fed to

the second phase.

In the second phase, polarity detection, the ERBA-DSL model proposed in the work[17] is utilized to find the polarity of the opinion expressed by the customer during chatbot-customer conversation. The model [17] performs sentiment analysis using intensifier-based polarity computation



**Figure 3.2 Proposed System Architecture**

The process of detecting sentiment polarity in chatbots is depicted in the figure. The chatbot user interface retrieves the text from the customer service inquiry and feeds it into the pre-processing module. Here, different pre-processing subtasks like case conversion, stop word removal, tokenization, and stemming are performed to prepare the text for analysis. The preprocessed text is supplied into the subjectivity detection module, where it is tagged with the proper grammatical counterparts (nouns, adjectives, verbs, etc.) using a PoS tagger. This module determines whether or not the text is subjective. Sentiment originates from subjective texts. Finding the different kinds of adverbs connected to the sentiment using trilateral modifiers is the next job. The true tone of the sentiment can be discerned based on the modifiers' potential to intensify. Ultimately, the framed nonary scale is used to apply the chatbot sentiment polarity detection, which accurately determines the tone and polarity of the sentiment conveyed in the text.

By building on the work of [22], the suggested technique for chatbot sentiment analysis has framed equations for generating sentiment scores.

Let SBT denote the sentiment-bearing term.

Let EN denote an enhancer-type modifier,

Let EM denote an emphasizer-type modifier

Let RE denote a reducer-type modifier

Let SBT\_EN denote a sentiment-bearing term associated with an enhancer-type modifier

Let SBT\_EM denote a sentiment-bearing term associated with an emphasizer-type modifier

Let SBT\_RE denote a sentiment-bearing term associated with a reducer-type modifier

Let SC stand for the sentiment score and W for the modifier's weight, which is a number between 0 and 1. The sample equations created as part of the suggested methodology for chatbot sentiment analysis are (1), (2), and (3) below. These three equations relate to positive adjectives and verbs. In a similar vein, negative adjectives and verbs were also handled via equations.

$$SC\_SBT\_EN = SC\_SBT + (1 - SC\_SBT) * W(EN) \tag{1}$$

$$SC\_SBT\_EM = SC\_SBT + (1 - SC\_SBT) * W(EM) \tag{2}$$

$$SC\_SBT\_RE = SC\_SBT + (1 - SC\_SBT) * W(RE) \tag{3}$$

Below is a sample of the pseudocode created for sentiment polarity detection:

...

// Input: User's inquiry (UI) to chatbot

// Output: Polarity Orientation (PO) of the sentiment inherent in the user inquiry and Sentiment score (SC)

// Let EN denote an enhancer-type modifier

// Let EM denote an emphasizer-type modifier

// Let RE denote a reducer-type modifier

// For every sentiment-bearing term (SBT) present in UI do

for each SBT in inquiry UI:

    // Check if SBT has any associated adverb/verb (M)

    if SBT has associated modifier M:

        // Determine the type of modifier and the sentiment of SBT

        switch (type of M):

            case EN and SBT is positive:

                Customer sentiment = "Extremely strong positive"

```

        SC = compute_score_using_equation1(SBT)
        break
    case EM and SBT is positive:
        Customer sentiment = "Strong positive"
        SC = compute_score_using_equation2(SBT)
        break
    case RE and SBT is positive:
        Customer sentiment = "Almost positive"
        SC = compute_score_using_equation3(SBT)
        break
    // Add more cases as needed for other combinations of M and SBT
end switch
else:
    // Assign the score SC from SentiWordNet lexicon based on SBT's sentiment
    SC = assign_score_from_SentiWordNet(SBT)
end if
end for
...

```

## 4. RESULTS AND DISCUSSION

Python language was used in the implementation of code in the Jupyter notebook provided by Google colab.

### 4.1 Performance metrics

The evaluation process employed three metrics: precision, recall, and F1-score. Precision is the ratio of the number of correctly detected sentiment polarity instances to the total number of detected instances; recall is the fraction of the number of correctly detected sentiment polarity instances to the actual number of correct instances; and F1-score is the geometric mean of precision and recall, which is used to achieve balance between the two metrics.

### 4.2 Data Acquisition

Using Twitter's application programming interface (API), social media tweets were crawled to get the data needed for the model evaluation. The following are the steps needed to use Python to collect data from tweets:

Step 1: Make an app and register for a Twitter developer account.

Step 2: To use the API, install the Tweepy Python module.

Step 3: Verify the requests made to the Twitter API are authentic.

Step 4: Use Tweepy to launch the tweets.

Step 5: Filter the tweets using hashtags or product/service terms, or refine them based on particular keywords like chatbots and bots.

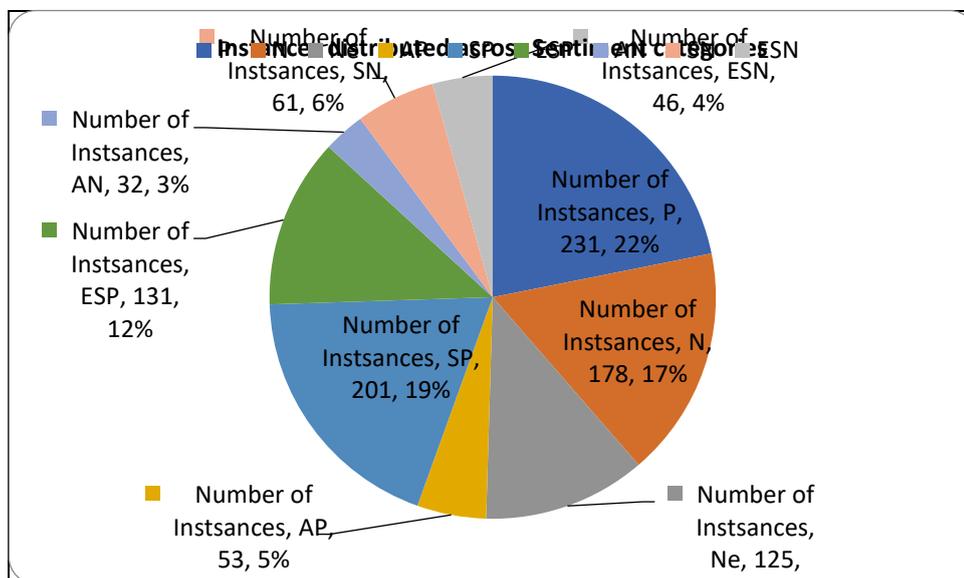
The aforementioned procedures were used to group tweets into the categories of fashion and telecoms. The dataset summary is displayed in table 4.1 below.

**Table 4.1 Dataset Statistics**

Sector	Number of tweets collected
<b>Garments</b>	720
<b>Telephony</b>	338

**4.3 Evaluation**

Assessing the performance of a chatbot is crucial, focusing on two main parameters: content evaluation and customer satisfaction [16]. Content evaluation originates from information retrieval and NLP research fields and involves tailoring the chatbot's replies to customer service inquiries. Conversely, customer satisfaction is the most frequently used metric for evaluating chatbot performance, as responses can vary with no single correct answer. The effectiveness of the chatbot is judged based on how pleased the customer is with the interaction. Customer satisfaction is a more appropriate measure for performance assessment since it reflects the customers' perspective on whether the responses meet their needs. Figure 4.1 illustrates the sentiment polarity distribution of 1058 instances (720 tweets related to fashion and 338 tweets related to telecommunications) using a nonary scale.



**Figure 4.1 Distribution of Instances over the nonary scale**

Samples are shown to be scattered throughout different sectors of positive polarity in picture 4.2 and across different sectors of negative polarity in figure 4.3.

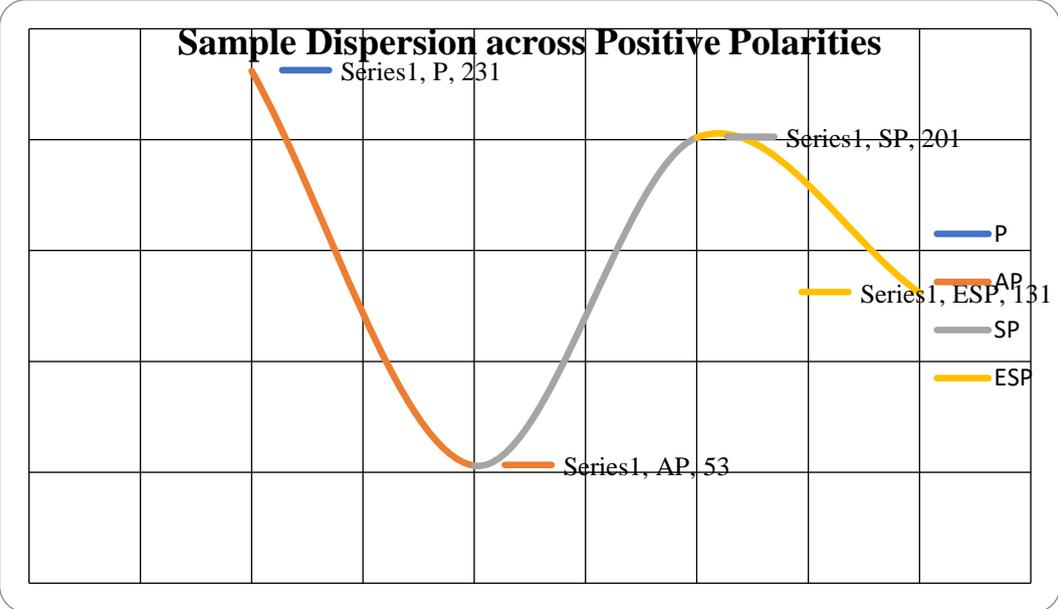


Figure4.2 Scattering of samples across positive polarities

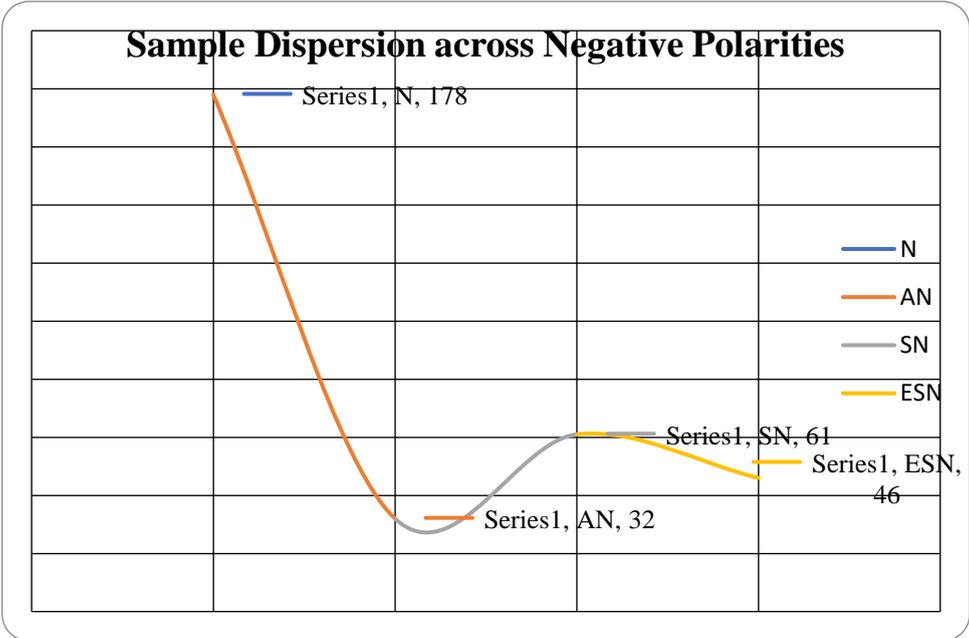
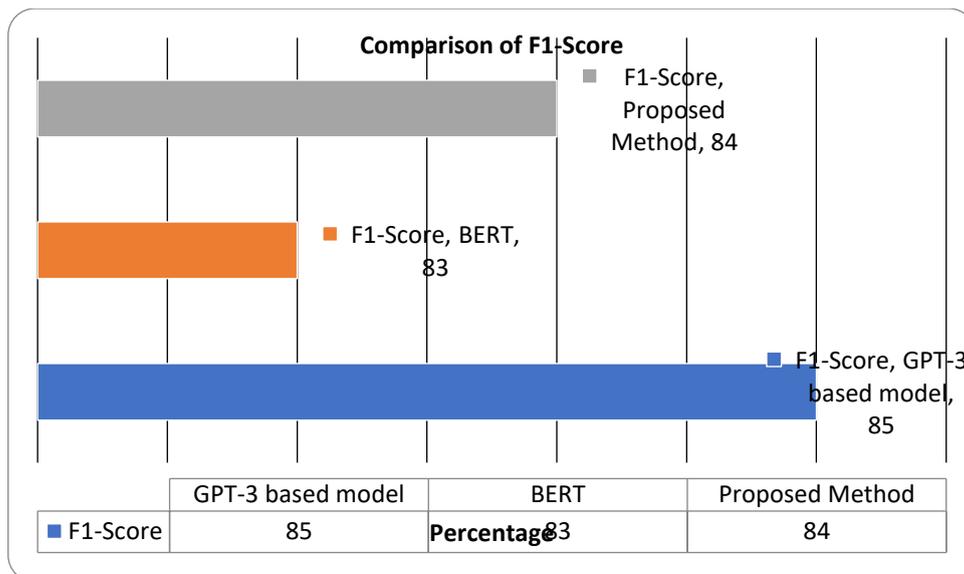


Figure 4.3 Scattering of samples across negative polarities



**Figure 4.4 Comparison of F1-score of the proposed method with the Existing GPT and ELMO methods**

A study using GPT-3 for chatbot sentiment analysis reported an F1-score of about 85%, indicating the model’s proficiency in understanding and classifying sentiments in conversational settings. Research utilizing BERT models for sentiment analysis in chatbot interactions has yielded F1-scores between 78-83%. One particular study found an F1-score of 80 when applying BERT to chatbot conversation datasets. The proposed work achieves a reasonably good F1-score of 84% and the comparison is shown in figure 4.4.

### 4.4 Comparative Analysis

#### 4.4.1. Computational Efficiency

The proposed model is designed specifically for sentiment analysis using a nine-point scale, it may have a more streamlined architecture compared to GPT-3 and BERT, which are general-purpose models. This specialization likely results in reduced computational overhead, making the proposed model more efficient in terms of processing time and memory usage.

The reduced complexity of the proposed model leads the way to achieve a high F1-score (84%) with fewer computational resources, making it more suitable for deployment in resource-constrained environments. GPT-3, is a large and complex model, leading to high computational costs. GPT-3’s computational efficiency is lower due to its massive size, requiring powerful hardware for inference and training, leading to higher operational costs. BERT, is smaller than GPT-3 but still relatively large. Its bidirectional attention mechanism increases computational complexity, especially during inference.

#### 4.4.2. Ease of Integration

The proposed model is likely easier to integrate into existing systems that require sentiment analysis. The simplicity of the model design, focused on the nine-point sentiment scale, allows for straightforward implementation without needing extensive customization or tuning. While GPT-3 offers versatility, the

integration process may require substantial effort in terms of optimizing performance and ensuring compatibility with existing infrastructure. BERT is easier to integrate than GPT-3 due to its smaller size and more focused application on NLP tasks. However, fine-tuning BERT for sentiment analysis might still require some expertise, particularly in optimizing the model for specific domains. The ease of integration with BERT is moderate, as it strikes a balance between versatility and complexity. It may require some customization but is generally more manageable than GPT-3.

#### 4.4.3. Scalability

The specialized design of the proposed model makes it highly scalable, particularly for applications focused on sentiment analysis. Its efficiency allows it to scale across different platforms, including mobile and edge devices, without significant loss of performance. Scaling GPT-3 across multiple devices or platforms requires significant infrastructure investment, making it less practical for widespread deployment, especially in environments with limited resources. BERT offers better scalability than GPT-3 due to its smaller size, but it still faces challenges when scaling across different environments. The model can be fine-tuned for specific tasks, allowing for more efficient scaling, but it may require careful resource management to avoid bottlenecks.

### 4.5 Real world Validation

As part of the research, customer queries and text were collected from garments and telephony domains and used for validating the proposed model. The table 4.2 presents some of the user queries and the corresponding responses generated by our model.

**Table 4.2 Sample Chatbot Responses**

#	User Input	Sentiment Analysis	Chatbot Response
1	"I'm extremely happy with the quality of the shirt I bought!"	Positive sentiment with an emphasize-type modifier (EM). High positive score.	"That's fantastic to hear! We're thrilled that you're extremely happy with your purchase. Is there anything else we can assist you with today?"
2	"Do you have this jacket in a smaller size?"	Neutral sentiment.	"Let me check that for you! Could you please provide the product code or name of the jacket?"
3	"I'm slightly disappointed with the fit of the pants."	Negative sentiment with a reducer-type modifier (RE). Mildly negative score.	"We're sorry to hear that the fit wasn't quite right. Would you like some assistance with sizing, or perhaps explore our return options?"
4	"The dress I ordered is beautiful."	Positive sentiment without modifiers.	"We're so glad you love the dress! Is there anything else you'd like to add to your wardrobe today?"
5	"The color is perfect, but I'm a bit concerned about the fabric quality."	Mixed sentiment with enhancer (EN) and reducer (RE). Mixed positive and negative scores.	"It's great that you love the color! Regarding the fabric quality, we assure you that we use top materials. However, if you have specific concerns, we're here to help."

6	"I need help deciding between these two jackets."	Neutral sentiment.	"I'd be happy to help! Can you provide more details about what you're looking for in a jacket, like style or material preferences?"
7	"The delivery was super fast, but the packaging was a bit damaged."	Mixed sentiment with enhancer (EN) and reducer (RE). Mixed positive and negative scores.	"We're glad the delivery was fast! However, we apologize for the packaging issue. Please let us know if any items were affected, and we'll assist you."
8	"I'm not satisfied with the quality of these jeans."	Negative sentiment without modifiers.	"We're sorry to hear that you're not satisfied with the quality. We take such feedback seriously and would love to make it right. Can we offer a solution?"
9	"The customer service has been excellent!"	Positive sentiment with emphasize-type modifier (EM). High positive score.	"Thank you for your kind words! We're delighted that you're pleased with our customer service. Is there anything else we can do for you today?"
10	"I love the design of the sweater, but it's a bit itchy."	Mixed sentiment with positive (love the design) and negative (itchy) aspects.	"We're happy to hear you love the design! Regarding the itchiness, it might soften after a wash, but if it's uncomfortable, we can explore other options."

### 4.6 Interpretability

The sentiment scores that are calculated using the nonary scale provide a nuanced understanding of the sentiment expressed in a chatbot's input. These scores can translate into chatbot responses. It involves mapping sentiment scores to response tones. The nonary scale likely ranges from -4 to +4, where negative values indicate negative sentiment, positive values indicate positive sentiment, and 0 indicates neutrality. The equations provided adjust the sentiment-bearing term (SBT) based on modifiers like enhancers, emphasize, and reducers. These adjustments provide a refined sentiment score (SC) for each term in the input.

**Positive Scores:** If the sentiment score (SC) is positive, the chatbot can generate responses that are supportive, encouraging, or optimistic. The intensity of the positivity could be linked to how high the score is on the positive side.

**Negative Scores:** If the sentiment score is negative, the chatbot could adopt a more empathetic, cautious, or consoling tone. The deeper the negative score, the more the chatbot could focus on addressing concerns or providing reassurances.

**Neutral Scores:** A neutral score (close to 0) might lead the chatbot to respond in a more factual or neutral tone, avoiding any overt emotional tone in its response.

#### Adjusting Responses Based on Modifiers

Enhancer-Type Modifier (EN):

- When an enhancer modifier is detected (e.g., "very"), the corresponding equation (1) increases the sentiment score. The chatbot can reflect this by amplifying its response tone. For instance, if the user says "very good," the chatbot might respond with a more enthusiastic or congratulatory tone.

Emphasizer-Type Modifier (EM):

- An emphasize modifier (e.g., "extremely") would also increase the sentiment score, as shown in equation (2). The chatbot could use stronger language or exclamations to match the heightened sentiment. For example, "extremely happy" might prompt the chatbot to respond with "That's fantastic!"

Reducer-Type Modifier (RE):

- A reducer modifier (e.g., "slightly") reduces the sentiment impact, as seen in equation (3). The chatbot can tone down its response accordingly. For example, if a user says "slightly disappointed," the chatbot might respond with a mild acknowledgment of the issue without overreacting.

#### Practical Implementation in Chatbot Responses

As the chatbot processes each input, it can calculate the sentiment score for each term and modifier in real-time. This score can then inform how the chatbot constructs its response, ensuring that the tone matches the user's sentiment. By using the nonary scale, the proposed model can offer a wide range of response tones, from highly positive to strongly negative, with subtle variations in between. This allows the chatbot to engage in more natural and human-like conversations. The chatbot can also use these scores to customize responses based on context or user preferences. For example, a user who frequently expresses strong emotions might trigger more emotionally resonant responses, while a user with more neutral expressions might receive more factual or balanced responses.

### 4.7 User Experience

The integration of an advanced sentiment analysis model using a nonary scale significantly enhances the overall user experience with chatbots. By refining the detection and interpretation of user sentiments, the chatbot can tailor its responses with greater accuracy and relevance. This personalization ensures that users feel understood and valued, which is crucial for increasing satisfaction. The ability to respond to subtle emotional cues helps in reducing user frustration and converting potentially negative interactions into positive outcomes. Moreover, the chatbot's improved sentiment analysis contributes to a more engaging and human-like interaction. Users are more likely to feel connected and comfortable when the chatbot adjusts its tone and content based on the emotional context of the conversation. This natural and empathetic communication style fosters a deeper level of engagement, enhancing the overall user experience. Consistency and reliability in responses are also key benefits of the sentiment analysis model. By maintaining contextually appropriate interactions, the chatbot builds trust and reliability with users. This trust, combined with proactive issue resolution—where the chatbot detects and addresses negative sentiments before they escalate—demonstrates attentiveness and responsiveness, further improving user satisfaction. In addition, the model supports a more natural conversational flow, which mimics human interactions more closely. Users appreciate conversations that feel less robotic and more genuine, leading to increased comfort and satisfaction. This human-like interaction not only enhances immediate user experiences

but also contributes to long-term user retention, as satisfied users are more likely to return and engage with the chatbot in the future. Overall, the advanced sentiment analysis model bridges the gap between technical performance and user-centric outcomes. By aligning the chatbot's responses with user emotions and needs, it ensures a more satisfying and engaging experience, thereby reinforcing the practical value of technical improvements in sentiment analysis.

## 5. CONCLUSION

The proposed work offers a deeper understanding of methods to enhance the competency of the customer care team by improving chatbot responses to client inquiries using sentiment analysis techniques. It covers the basics of chatbots, sentiment analysis, and Auto NLP for pre-processing customer inquiry text. The chapter also details a sentiment analysis-based methodology to enhance customer satisfaction with chatbot responses. The proposed methodology achieved an F1 score of 84%, thanks to the fine-tuned measurement of customer sentiment polarity using trilateral modifiers and a nonary scale.

## REFERENCES

1. Kamath, Rajani&Jamsandekar, Shruti&M.B.Patil, Mr. (2020). Chatbot Response Mining using Sentiment Analysis.
2. Sentiment Analysis on Interactive Conversational Agent/ChatbotsSameenaThabassum
3. Sodré, Wagner & Duarte, Julio. (2023). Chatbot Optimization using Sentiment Analysis and Timeline Navigation. *Revista de Informática Teórica e Aplicada*. 30. 32-43. 10.22456/2175-2745.125825.
4. El-Ansari, Anas&benihssane, Abderrahim. (2023). Sentiment Analysis for Personalized Chatbots in E-Commerce Applications. *Wireless Personal Communications*. 129. 1-22. 10.1007/s11277-023-10199-5.
5. Aishwarya B R et al. SENTIMENT ANALYSIS FOR chatbots to make them emotionally reactive Vol-7 Issue-3 2021 IJARIII-ISSN(O)-2395-4396
6. Tran, Anh&Pallant, Jason & Johnson, Lester. (2021). Exploring the impact of chatbots on consumer sentiment and expectations in retail. *Journal of Retailing and Consumer Services*. 63. 102718. 10.1016/j.jretconser.2021.102718.
7. Feine, Jasper &Morana, Stefan &Gnewuch, Ulrich. (2019). Measuring Service Encounter Satisfaction with Customer Service Chatbots using Sentiment Analysis.
8. Ma Dongbo, Sami Miniaoui, Li Fen, Sara A. Althubiti, Theyab R Alsenani, Intelligent chatbot interaction system capable for sentimental analysis using hybrid machine learning algorithms, *Information Processing & Management*, Volume 60, Issue 5, 2023, 103440, ISSN 0306-4573, <https://doi.org/10.1016/j.ipm.2023.103440>.
9. Widyaningrum, Prima &Ruldeviyani, Yova&Dharayani, Ramanti. (2019). Sentiment Analysis to Assess the Community's Enthusiasm Towards the Development Chatbot Using an Appraisal Theory. *Procedia Computer Science*. 161. 723-730. 10.1016/j.procs.2019.11.176.
10. Lee, Chih-Wei & Wang, Yau-Shian& Hsu, Tsung-Yuan & Chen, Kuan-Yu & Lee, Hung-

- yi & Lee, Lin-shan. (2018). Scalable Sentiment for Sequence-to-sequence Chatbot Response with Performance Analysis.
11. H. N. Io, C. B. Lee, " Chatbots and conversational agents: A bibliometric analysis", Proceedings of IEEE International Conference on Industrial Engineering & Engineering Management 2017, Page(s): 215 – 219
  12. Vyas Ajay Bhagwat, "Deep Learning for Chatbots", SJSU Scholar Works Master's Projects Master's Theses and Graduate Research Spring 2018 San Jose State University
  13. Csaky, Richard., "Deep Learning Based Chatbot Models" , Scientific Students' Associations Report, Department of Automation and Applied Informatics, Budapest University Of Technology and Economics, (2017).
  14. DahiyaMenal, "A Tool of Conversation: Chatbot", International Journal Of Computer Sciences And Engineering. 5. 158-161.
  15. Sentiment Analysis, [https://en.wikipedia.org/wiki/Sentiment\\_analysis](https://en.wikipedia.org/wiki/Sentiment_analysis) retrieved on 18th Dec 2019.
  16. Maroengsit, W., Piyakulpinyo, T., Phonyiam, K., Pongnumkul, S., Chaovalit, P., &Theeramunkong, T. (2019). A survey on evaluation methods for chatbots.In Proceedings of the 2019 7th International conference on information and education technology (pp. 111–119).
  17. Devi Sri Nandhini, M. &Gurunathan, Pradeep. (2022). Efficacy improvement of aspect-based sentiment analysis using enhanced rule –based approach and domain-specific lexicon (ERBA-DSL). Journal of Intelligent &Fuzzy Systems. 43. 1-19. 10.3233/JIFS-213584.
  18. Marstawi, A, Sharef, NM, Aris, TNM & Mustapha, A 2017, Ontology-based aspect extraction for an improved sentiment analysis in summarization of product reviews', In Proceedings of the 8th International Conference on Computer Modeling and Simulation, pp. 100-104.
  19. Sindhu, I, Daudpota, S. M, Badar, K, Bakhtyar, M, Baber, J &Nurunnabi, M 2019, Aspect-based opinion mining on student's feedback for faculty teaching performance evaluation, IEEE Access, vol. 7, pp. 108729-108741.
  20. Singh, VK, Piryani, R, Uddin, A &Waila, P 2013, Sentiment analysis of movie reviews: a new feature-based heuristic for aspect-level sentiment classification, International Multi-Conference On Automation, Computing, Communication, Control And Compressed Sensing (IMAC4S) IEEE, pp. 712-717.
  21. Singh, VK, Piryani, R, Waila, P &Devaraj, M 2014, Computing sentiment polarity of texts at document and aspect levels, ECTI Transactions on Computer and Information Technology (ECTI-CIT), vol. 8, no. 1, pp. 67-79.
  22. Benamara, F, Cesarano, C, Picariello, A, Recupero, DR &subrahmanian, VS 2007, Sentiment analysis: Adjectives and adverbs are better than adjectives alone, ICWSM, vol. 7, pp. 203-206.
  23. M, Devi Sri Nandhini., Gurunathan, P. Joint aspect-opinion extraction and sentiment orientation detection in university reviews. *International journal of information technology*. **14**, 3213–3225 (2022).<https://doi.org/10.1007/s41870-022-01041-5>
  24. M.D. Devika, C. Sunitha, AmalGanesh,Sentiment Analysis: A Comparative Study on Different Approaches, Procedia Computer Science,Volume 7,2016,Pages 44-49,ISSN 1877-0509, <https://doi.org/10.1016/j.procs.2016.05.124>.

25. Qazi, A., Raj, R. G., Hardaker, G., & Standing, C. (2017). A systematic literature review on opinion types and sentiment analysis techniques: Tasks and challenges. *Internet Research*, 27(3), 608-630.
26. Schouten, K., & Frasincar, F. (2015). Survey on aspect-level sentiment analysis. *IEEE transactions on knowledge and data engineering*, 28(3), 813-830.
27. Wankhade, M., Rao, A. C. S., & Kulkarni, C. (2022). A survey on sentiment analysis methods, applications, and challenges. *Artificial Intelligence Review*, 55(7), 5731-5780.
28. Behdenna, S., Barigou, F., & Belalem, G. (2018). Document level sentiment analysis: a survey. *EAI endorsed transactions on context-aware systems and applications*, 4(13), e2-e2.
29. Shirsat, V. S., Jagdale, R. S., & Deshmukh, S. N. (2017, August). Document level sentiment analysis from news articles. In *2017 international conference on computing, Communication, Control and Automation (ICCUBEA)* (pp. 1-4). IEEE.
30. Meena, A., & Prabhakar, T. V. (2007). Sentence level sentiment analysis in the presence of conjuncts using linguistic analysis. In *Advances in Information Retrieval: 29th European Conference on IR Research, ECIR 2007, Rome, Italy, April 2-5, 2007. Proceedings 29* (pp. 573-580). Springer Berlin Heidelberg.