An Exploratory Study on the Sentiment Analysis of Users Towards Using Chatgpt

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Abstract:
ChatGPT boosts productivity and decision-making by offering immediate, precise information and individualised support. It can handle a wide range of duties, from creating material to deciphering intricate queries, making it a useful tool for both personal and business use. Sentiment analysis, also known as opinion mining, is a computational technique used to determine and classify the emotional tone expressed in text. The current study used a mixed-method approach. Structured data was analysed using a bar chart, and unstructured data was analysed using sentiment analysis (word cloud). It was seen that 65.91 % of respondents have given overall good rating towards ChatGPT and 34.09% of respondents have given poor rating towards ChatGPT. It was also seen that 45.45% respondents have given overall negative feedback towards ChatGPT and 54.55% of respondents have given positive feedback towards ChatGPT. Further it was also seen that respondents who had given negative feedback faced various problems and challenges viz. Inaccurate information, ethical concerns, language quality, sensitivity, technical, and creativity Limitations, response generations, linguistic mismatch, Research barriers, misunderstanding, cultural dependency and variability data.
Keywords: Sentimental Analysis, ChatGPT, Exploratory Study

1. Introduction:

Human-computer interactions have undergone a tremendous transformation with the introduction of sophisticated chatbots like ChatGPT. OpenAI's ChatGPT has quickly become well-known for its capacity to produce responses that resemble those of a human being and to handle challenging language challenges (Gilson et al., 2023; Talan & Kalinkara, 2023). ChatGPT is an advanced natural language processing (NLP) model that has wide applications in customer service, content development, and education. Intending to shed light on users' opinions and experiences with this innovative AI technology, this study intends to investigate how users feel about ChatGPT.

1.1 Sentimental Analysis

Texts are now useful sources of data when it comes to deriving subjective interpretations from information. Sentence subjectivity was examined by Hatzivassiloglou and Wiebe (2000) as they looked at the coherence of concepts in virtual settings. Moreover, Pang et al. (2002) showed that machine learning methods can be used to categorise emotions. As a result, useful information may now be extracted from online posts on events, circumstances, goods, services, or political opinions using opinion mining and sentiment analysis (Tuzcu, 2020). Sentiment analysis provides important information on a wide range of social characteristics, from political views to product or service satisfaction, and can help inform precise and efficient decision-making.

Classification algorithms are trained on a pre-labeled opinion data set in sentiment analysis to create class models using machine learning techniques. Next, the sentiment of fresh data can be detected using the resulting model. To find opinions in the data set, lexicon-based techniques generate dictionaries of opinion words or use ones that already exist (Onan, 2017). The LIWC (Pennebaker, Francis, & Booth, 2001), EmosenticNet (Poria et al., 2012), NRC (Mijwil et al., 2023), DepecheMood (Staiano & Guerini, 2014), and Empath (Aljanabi et al., 2023) are sentiment dictionaries that are often used. EmosenticNet covers Disgust, Joy, Fear, Surprise, Anger, and Sadness; LIWC defines emotions as Positive, Negative, Sadness, and Anger. While NRC identifies Trust, Anticipation, Disgust, Joy, Fear, Surprise, Anger, Sadness, and Love, Empath classifies emotions into Joy, Fear, Surprise, Anger, Sadness, and Love (Atlı & İlhan, 2021). Researchers frequently utilise numerous dictionaries or construct new ones based on preexisting classifications because emotion detection is not always perfect. For instance, Atlı and İlhan (2021) created the lexicon NAYALex, which categorises 38 emotions from the dictionaries of the NRC, EmosenticNet, DepecheMood, LIWC, and Empath.

1.2 Chatbots and ChatGPT

Chatbots are artificial intelligence (AI) programmes that mimic human communication by processing text or voice queries and are designed to accurately respond to user inquiries (Özkol, Doğan, & Köseali, 2019). Because they provide consumers with infinite time for interaction, they provide benefits in marketing and customer relations. After being released on November 30, 2022, ChatGPT (Chat Generative Pre-trained Transformer), a chatbot created by OpenAI, garnered a lot of popularity very soon. One of the largest language models, this sophisticated NLP model has 175 billion parameters and was optimised through the use of supervised and reinforcement learning approaches (Cotton, Cotton, & Shipway, 2023). ChatGPT can read and write text by using the GPT-3 text interpreter (Pavlik, 2023). Although ChatGPT was first created for online customer relations, its uses are not limited to customer service (Gilson et al., 2023; Qadir, 2022). It can be used in fields including software development, content production, language translation, education, and healthcare consultation. It can also build programme code for particular algorithms or calculations and generate articles in many languages. Given ChatGPT's wide range of applications, it is likely that the use of AI chatbots will increase along with their popularity.

The potential of ChatGPT is highlighted by recent scientific investigations. For children's foreign language instruction, Topsakal and Topsakal (2022) suggested a software architecture utilising ChatGPT and augmented reality (Topsakal & Topsakal, 2022). When Kung et al. (2022) assessed ChatGPT's performance on US medical exams, they discovered that it could pass three exams without the need for specialised training, demonstrating its potential for use in clinical decision support and medical education (Kung et al., 2023). When Gao et al. (2022) used ChatGPT to create study summaries from high-impact medical abstract titles and journals, they found that ChatGPT was able to successfully construct summaries that plagiarism checkers could not identify (Gao et al., 2022).

2. Review of Literature:

2.1 Tubishat, M., et al. (2023). The study used data gathered from Twitter to determine prevalent attitudes, subjects, and viewpoints expressed on the usage of ChatGPT in education. 11,830 tweets were analysed, and the majority of opinions of ChatGPT in education were either good or neutral. Few opinions were negative. To analyse sentiments, the study used four classifiers: Random Forest, K-Nearest Neighbours, Support Vector Machine (SVM), and Naive Bayes. At 81.4%, the SVM classifier had the best accuracy. Additionally, the study identified the most often used terms in both favourable and negative opinion tweets, offering valuable information about how educators generally see ChatGPT.

2.2 Munggaran, J. P., et al. (2023). The study sought to assess the accuracy of the sentiment analysis models as well as the opinions of Twitter users on ChatGPT's use in education. By using the RapidMiner Studio tool to gather and label data from Twitter, the study was able to classify attitudes as positive or negative based on the occurrence of specific words. The findings helped to clarify public opinion by shedding light on how Twitter users felt generally about ChatGPT in the classroom. In evaluating the possible effects of ChatGPT on academic integrity and the school environment, these findings are helpful for educators and legislators.

2.3 Mohammad, Belal., et al. (2023). The study compared ChatGPT's performance against conventional lexicon-based unsupervised approaches in order to assess how well it works for data labelling in sentiment analysis tasks. Twitter and Amazon reviews are two different sentiment analysis datasets that were used in the study to test ChatGPT. The outcomes demonstrated that ChatGPT performed noticeably better than lexicon-based unsupervised techniques. On the Twitter dataset, ChatGPT produced an accuracy gain of 20%; on the Amazon reviews dataset, the improvement was closer to 25%. These results show that ChatGPT can efficiently label data for sentiment analysis, providing notable gains in accuracy over current lexicon-based methods. According to the study, ChatGPT is a very useful tool for annotation in a range of sentiment analysis applications.

2.4 Adem, Korkmaz.,et al. (2023). The purpose of the study was to perform a sentiment analysis of tweets on Twitter that had something to do with ChatGPT in the first two months after its debut in order to gain a thorough understanding of the early thoughts and feelings of users who discovered the platform. 788,000 English tweets were subjected to sentiment analysis using the AFINN, Bing, and NRC dictionaries. The results showed that a sizable percentage of first-time users were satisfied and thought their experience with ChatGPT went well. Some users did, however, also describe unfavourable feelings like worry and fear. The most thorough sentiment analysis of ChatGPT to date was offered by this study, which also recommended that future studies concentrate on ChatGPT's effectiveness in particular domains.

2.5 R., S., Mujahid, et al. (2023). The purpose of the study was to evaluate public perceptions of the tool's merits and drawbacks by examining the tone and subjects of tweets about ChatGPT. To conduct the study, tweets from Twitter that included the hashtags for ChatGPT—user reviews and opinions—had to be extracted. The themes that were mentioned the most in these tweets were determined by applying the Latent Dirichlet Allocation (LDA) technique. Three dense layers of neural networks in a deep transformer-based Bidirectional Encoder Representations from Transformers (BERT) model were proposed for sentiment analysis. Additionally, a comparative analysis was carried out with a variety of machine and deep learning models that had been adjusted for parameters. With an accuracy of 96.49%, the experimental findings showed that the suggested BERT model performed better than expected.

2.6 Machálíková, K. (2023). The purpose of the study was to investigate the use of ChatGPT for sentiment analysis, with an emphasis on consumer views and feelings about products, services, or businesses in general, and how this data can affect corporate decision-making. The theoretical underpinning of the study was derived from a variety of literary sources and was reinforced by actual case studies. It was highlighted that undertaking sentiment analysis about privacy and data protection is essential for businesses to operate ethically. The sampled cases showed that ChatGPT could carry out sentiment analysis as directed and interpret text straight from screenshots.

2.7 Rochadiani, T. H. (2023). This study's main goal was to find out how well consumers accepted ChatGPT, a novel artificial intelligence tool. The purpose of the study was to ascertain people's opinions and enthusiasm regarding ChatGPT, which could influence future advancements in artificial intelligence. Sentiment analysis was used in the study on a sizable dataset of YouTube user comments. Following pre-processing of the data to eliminate stop words, punctuation, and superfluous information, TextBlob and VADER techniques were used to categorise comments into three groups: positive, neutral, and negative. The majority of users expressed positive views towards ChatGPT, according to the results.

2.8 Koonchanok, R., Pan, Y., & Jang, H. (2023). This study set out to find out how the general population felt about ChatGPT, a sophisticated chatbot that uses a large language model (LLM). The study employed natural language processing methods on Twitter data from December 5, 2022, to June 10, 2023, including sentiment analysis and topic modelling. On Twitter, the general opinion of ChatGPT was primarily neutral to favourable. Throughout the examined period, negative attitudes shown a declining trend. The analysis pinpointed several often discussed ChatGPT-related subjects, such as marketing, cybersecurity, education, bard, search engines, and open AI. These subjects' popularity and rankings changed every month.

3. Research Methodology

Table No: 1 Research Methodology

Research Design	Exploratory
Research Approach	Mixed-method approach. Structured data was analysed using a bar chart, and unstructured data was analyzed using sentiment analysis (word cloud).
Data Collection	Primary and Secondary
Sampling Technique	Non-Probability Convenient Sampling
Sample Size	44 Research Scholars from North Mumbai Region.
Statistical Technique	Text Mining
Statistical Tool	Python

Table No: 2 Demographic Profile

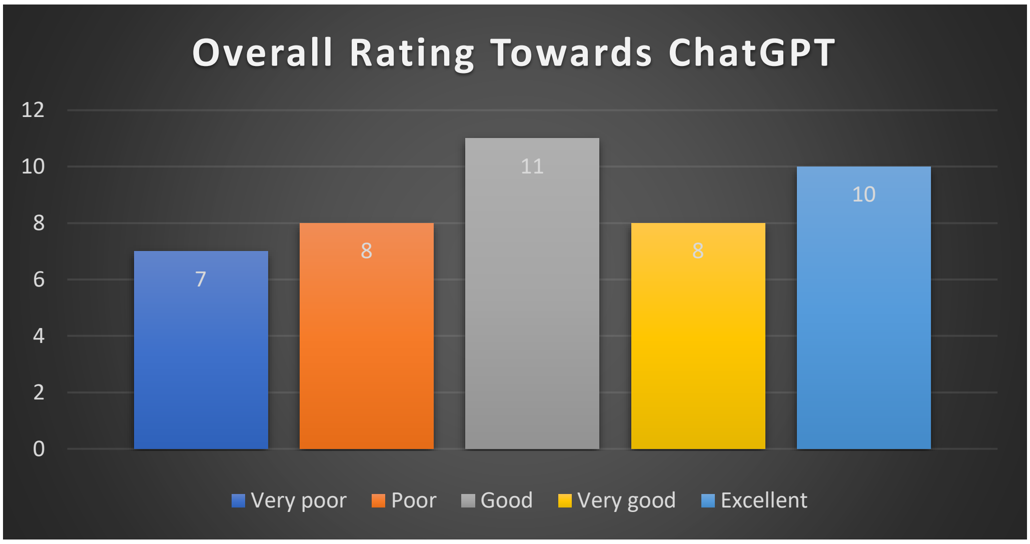
Category	Variables	Frequency	Percentage
Gender	Male	23	52.27
	Female	21	47.73
Age	25 to 35 years	8	18.18
	36 – 45 years	15	34.09
	46 – 55 years	12	27.27
	56 and above	9	20.46
Stream	Commerce	15	34.09
	Science	15	34.09
	Arts	14	31.82

Data was collected from 44 research scholars to understand their sentiment towards ChatGPT usage. It was seen that there are 23 (52.27%) males and 21 (47.73%) females. The respondents' age category was seen as 8 (18.18%) in the age bracket of 25 – 35 years, 15 (34.09%) in 36 – 45 years category, 12 respondents (27.27%) in 46 – 55 years and 9 (20.46%) are above 56 years. 15 (34.09%) Research scholars belong to the commerce and science stream whereas 14 (31.82%) belong to the Arts stream.

Table no: 3 Count of Overall Rating Towards ChatGPT

Overall Rating	Frequency	percentage
Very poor	7	15.91
Poor	8	18.18
Good	11	25.00
Very good	8	18.18
Excellent	10	22.73

Figure no: 1 Count of Overall Rating Towards ChatGPT

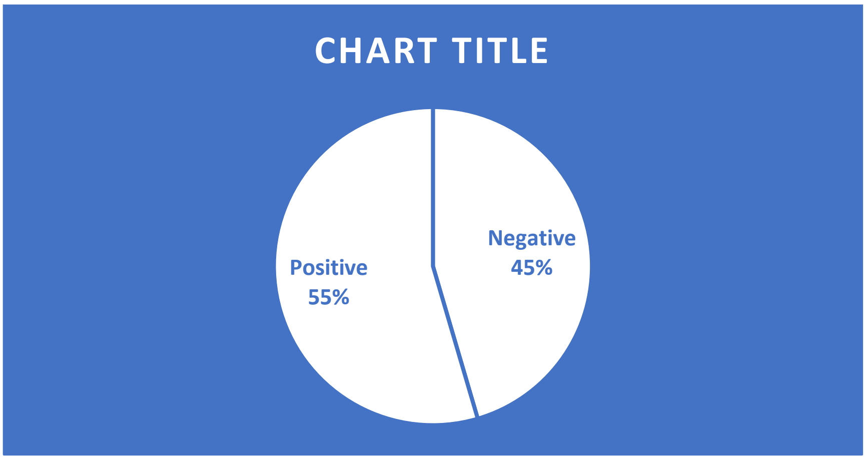


A substantial majority (54.55%) of respondents expressed high levels of happiness, as seen in the figure depicting their satisfaction. Most of the respondents i.e., 11 or 25.00 % rated good, 10 or 22.73% rated excellent and 8 Respondents with 18.18 % rated very good to to theirs satisfaction towards ChatGPT overall impression of their time there. According to the data, there appears to be a positive pattern among the respondents towards their overall rating towards ChatGPT.

Table no: 4 Count of Respondents Feedback

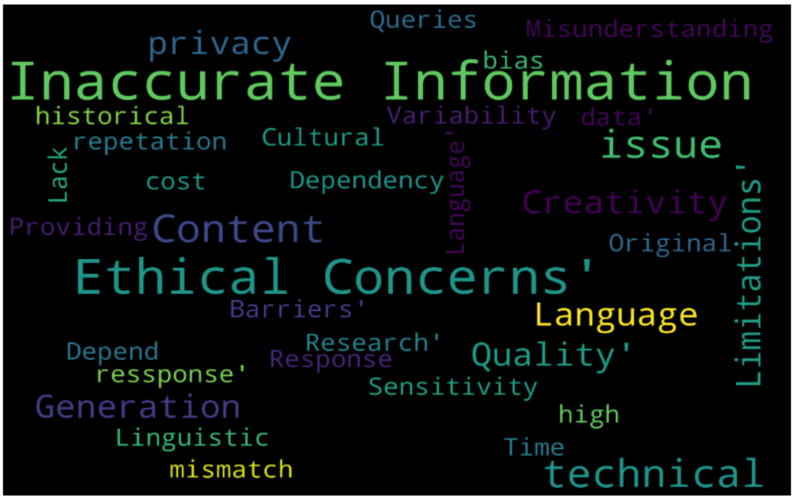
Feedback	Frequency	Percentage
Negative	20	45.45%
Positive	24	54.55%

Figure no: 2 Pie Diagram of Respondents Feedback



From the above figure No: 2 it can be seen that the majority of the respondents i.e. 25 put of 44 respondents i.e. 54.55% gave positive feedback on their overall satisfaction towards using ChatGPT. This positive sentiment suggests that the users are overall satisfied with the usage of ChatGPT.

Figure No: 3 Word Cloud



A word cloud is a visual representation of text data made up of words displayed in different sizes, each of which symbolises a word's relevance or frequency within the dataset. It gives you a quick and easy way to find the most important themes or keywords in a document, giving you important information about recurring themes, trends, or attitudes.

The above word cloud indicates the negative rating given by the respondents to the problem that the 20 users face while using ChatGPT. It can be observed that Inaccurate information, ethical concerns, language quality, sensitivity, technical, and creativity Limitations, response generations, linguistic mismatch, Research barriers, misunderstanding, cultural dependency and variability data are some of the problems faced by the users of ChatGPT.

4. Conclusion

1. Modern libraries, Python coding with the inventors' loop, Google Colab Note Book, and word cloud synthesis were also utilised. Because of this, the provided procedure is scientific and yields the sentiment's real result.
2. The majority of the users of ChatGPT (54.55%) had a positive response towards their satisfaction with the application. This can be seen in figure no. 1 Bar Diagram of Respondents Feedback.
3. It was also seen that (44.45%) had a negative response towards their satisfaction with the ChatGPT. This can be observed in figure no. 2 Pie Diagram of Respondents Feedback.
4. The figure no. 3 word cloud the negative rating given by the respondents to the problem that the users face while using ChatGPT can be observed. Inaccurate information, ethical concerns, language quality, sensitivity, technical, and creativity Limitations, response generations, linguistic mismatch, Research barriers, misunderstanding, cultural dependency and variability data are some of the problems faced by the users of ChatGPT.

5. Suggestions:

- Update and verify the data sources frequently. Increase the level of detail of the information provided in validation tests.
- Incorporate moral principles and openness on the usage of data. Make it clear what the AI's limitations and applications are.
- Improve language models to better manage context, tone, and grammar. Provide a variety of writing styles and tones to accommodate the preferences of the user.
- Provide more thorough instruction to help people respect and comprehend different viewpoints and cultures. To lessen biases and boost sensitivity, update the model often.
- Optimise the system to handle complex queries more effectively and to respond to requests more quickly. Make sure the platform is usable and accessible on various networks and devices.
- Introduce techniques or resources for creative writing to aid in brainstorming and the generation of original ideas. Permit users to give more background or preferences to influence the answers.
- Improve translations for non-English languages and multilingual support. Improve how informal language and regional dialects are handled.

- Give users access to integrated research tools or connections to reliable sources to help them locate correct information. Promote cooperation with academic establishments to enhance research proficiencies.
- Provide a feedback loop so that consumers can ask more questions if the first response doesn't satisfy them. To guarantee greater comprehension, include interactive components like guided questions.
- Update the model often using a variety of cultural expertise to deliver more considerate and pertinent solutions. Gather input from end users across the globe to comprehend and incorporate diverse cultural differences.

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