AI in the Public Eye: Analysing Social Media Sentiment and Opinion on Artificial Intelligence

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Abstract: Artificial Intelligence (AI), a rapidly evolving technology with far-reaching implications, has become a widely discussed topic on social media platforms. This study conducted a comprehensive sentiment analysis of posts discussing AI topics on Twitter, YouTube and Reddit from 2017 to 2024 to evaluate public perceptions and attitudes toward AI. A total of 133,004 social media posts were analysed using a fine-tuned RoBERTa model for sentiment classification, alongside Latent Dirichlet Allocation (LDA), n-gram, and word co-occurrence mapping for topic modelling. The analysis revealed that 46.09% of the posts express negative sentiments about AI, followed by 39.29% neutral and 14.62% positive sentiments. LDA uncovered 20 key topics, including AI ethics, job impacts, and philosophical implications. Temporal analysis revealed a significant surge in AI-related discourse from 2022 onward, with evolving sentiment patterns. These findings suggest a complex landscape of public AI perception, reflecting persistent concerns about societal impacts alongside increasing interest in AI's technical aspects.

Keywords: Artificial intelligence, Sentiment analysis, Social media, Natural language processing, Topic modelling, Public perception

1. Introduction

The rise of artificial intelligence (AI) has sparked a global dialogue, with social media platforms serving as pivotal arenas for the exchange of opinions and sentiments [1]. As AI becomes an integral part of daily life, policymakers, researchers, and industry stakeholders must understand public perceptions and sentiments toward this disruptive technology [2, 3]. Sentiment analysis, also known as opinion mining, is a technique used to identify and categorise opinions in text, determining whether the sentiment is positive, negative, or neutral [4, 5]. Sentiment analysis techniques are not just tools, but powerful instruments for analysing the factors that shape public attitudes, concerns, and expectations regarding AI. These insights enable informed decision-making and the development of tailored communication strategies [1]. The exponential growth of social media platforms has fostered an environment conducive to the free expression of opinions and provided a rich and diverse data source for sentiment analysis and opinion mining [3, 6]. Platforms such as Twitter, Facebook, and Reddit have become virtual town halls where individuals share their thoughts, experiences, and concerns about AI's impact on various domains, including employment, privacy, ethics, and societal implications [2, 7, 8]. By utilising sentiment analysis and opinion-mining methods, researchers can gain valuable insights into the public views of AI, enabling a deeper understanding of the factors shaping these sentiments and opinions [6]. This paper presents a comprehensive sentiment analysis of posts discussing AI topics (AI-related posts) on Twitter, YouTube, and Reddit from 2017 to 2024, aiming to assess public perceptions and attitudes toward AI. To provide a clear structure, the paper begins with a review of related work, followed by an explanation of the approaches employed for data collection and analysis. Finally, the findings are presented, offering insights into public perceptions and attitudes toward AI over the studied period.

2. Related Work

2.1. Sentiment Analysis and Natural Language Processing (NLP)

Sentiment analysis approaches in Natural Language Processing (NLP) can be broadly divided into three categories: lexicon-based, machine learning-based, and hybrid methods, as shown in Figure 1. Traditional approaches include lexicon-based methods like VADER and TextBlob [1, 9], which are interpretable but struggle with context-specific language, particularly in AI-related discussions. To address these limitations, machine learning-based techniques, such as Naïve Bayes and Support Vector Machines, and deep learning models like CNNs and RNNs, have emerged, offering improved sentiment prediction. However, they require substantial labelled data for effective training [10]. To further enhance robustness, hybrid methods have been developed, combining the strengths of both lexicon-based and machine learning approaches [5, 11]. Recent advancements in machine learning, particularly in transfer learning, using pre-trained models like BERT and RoBERTa, have significantly improved accuracy, especially in nuanced contexts [12].

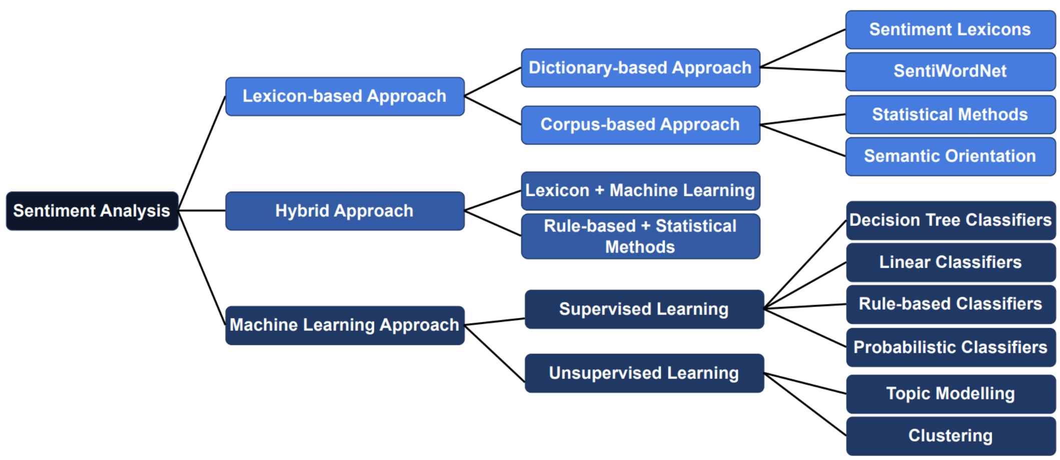

Figure 1. Overview of key approaches to sentiment analysis, including lexicon-based methods, machine learning models, and hybrid techniques.

2.2. Artificial Intelligence and Public Perception

Public perception of AI has evolved significantly, shaped by media, science fiction, and real-world developments [13]. Initially influenced by science fiction, public attitudes fluctuated between optimism during AI's early successes and scepticism during the "AI winters" [14, 15]. However, the proliferation of AI in the 21st century, from virtual assistants to autonomous vehicles, has reignited interest and raised ethical, social, and economic concerns [16]. Social media platforms have emerged as vital sources for gauging public sentiment, revealing an evolving landscape of optimism about AI's potential benefits and persistent concerns about issues such as privacy, bias, and job displacement [17–19]. Recent research has highlighted the dual nature of public perception toward AI, where enthusiasm for its transformative potential is frequently balanced by concerns about societal consequences. Building on this foundation, our study extends beyond prior work—such as the analysis of post-ChatGPT Reddit data [20] or Twitter data [21]—by examining AI discourse across multiple platforms (Twitter, Reddit, and YouTube) over a broader timeframe (from 2017 to 2024). This longitudinal, cross-platform approach not only captures perceptions before and after ChatGPT's emergence but also provides a more nuanced understanding of how public attitudes toward AI in general have evolved, addressing limitations of single-platform or narrowly temporal studies

2.3. Emerging Trends in Social Media Data Analysis

Recent advancements in social media data analysis highlight three key trends: multimodal analysis, real-time analysis, and explainable AI. As social media content increasingly integrates text, images, and videos, multimodal approaches have gained importance. Baltrušaitis et al [22] survey multimodal machine learning techniques, focusing on challenges in fusion and cross-modal learning. These approaches are particularly useful for analysing AI-related content, which often includes visual elements like infographics or video demonstrations. The dynamic nature of social media necessitates real-time analysis. Bifet and Frank [23] explore stream mining techniques, addressing challenges such as concept drift and computational resource limitations. Wang et al [24] propose edge computing architectures for handling high-volume social media data streams. Real-time analysis is critical for tracking rapidly evolving AI discussions, especially in response to breaking news or significant technological advancements. The complexity of modern machine learning models has increased the focus on interpretability and explainability. Gilpin et al [25] review explainable AI techniques in deep learning, emphasising their relevance to social media analysis. Model interpretability enhances trust in AI systems and supports informed decision-making based on social media insights. This is particularly important in AI-related sentiment analysis, where understanding the reasoning behind sentiment classifications can help stakeholders contextualise trends and patterns [1, 24, 26].

3. Approach & Study Design

This study employed a mixed-methods approach, combining quantitative and qualitative techniques to investigate public perception and discourse surrounding artificial intelligence (AI) on social media platforms. The research design encompassed data collection, pre-processing, sentiment analysis, topic modelling, temporal analysis, and visualisation of results, as shown in Figure 2.

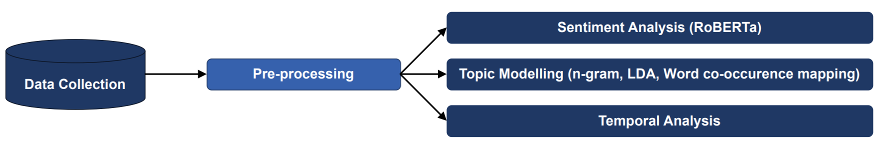

Figure 2. Overview of the mixed-methods approach used to analyse public perception of AI in social media.

3.1. Data Collection

Data was collected from three major social media platforms: Twitter, YouTube, and Reddit. Twitter data was gathered using the Tweepy library with access to Twitter API [27]. Tweets containing AI-related keywords and hashtags were retrieved, including text, user information, timestamps, and geolocation (when available). AI-related posts were identified using a comprehensive set of keywords including: "artificial intelligence", "AI", "machine learning", "deep learning", "neural networks", "ChatGPT", "GPT", "LLM", and platform-specific hashtags such as #AIethics, #AIresearch, and #MachineLearning. This keyword selection strategy ensured broad coverage of AI-related discussions while minimising irrelevant content. YouTube data was collected using the YouTube Data API [28], using the same relevant keywords, retrieving video metadata, such as titles, descriptions, comments, and view counts. Reddit data were accessed using the Python Reddit API Wrapper (PRAW) [29], enabling the retrieval of submissions and comments from various AI-related subreddits specifically related to AI, including r/ArtificialIntelligence, r/MachineLearning, and r/ChatGPT. In total, our dataset comprised over 133,000 social media posts spanning from 2017 to 2024, providing a comprehensive temporal range for analysis of public sentiment evolution.

3.2. Data Pre-processing

The raw data was pre-processed using NLTK [30] and Stanford CoreNLP [31], removing irrelevant elements like URLs, special characters, and emojis, while handling user mentions and hashtags appropriately. The text was tokenised, lowercased, and stripped of stop words using NLTK's predefined list. Byte-level Byte-Pair Encoding (BPE) was applied for tokenisation, handling informal social media text without the need for traditional stemming and lemmatisation [32]. This approach was chosen specifically because it effectively handles the diverse vocabulary and informal language common in social media posts, including misspellings, abbreviations, and platform-specific conventions. Bot-generated content was filtered using a combination of pattern matching and user activity heuristics to ensure the analysis captured genuine human opinions rather than automated messaging. This filtering process removed approximately 8% of the initially collected data.

3.3. Sentiment Analysis

Sentiment analysis was performed using Twitter-roBERTa-base[1] [33, 34], a transformer-based model fine-tuned for social media text sentiment analysis. This model was selected following an evaluation process that considered both its domain-specific advantages and comparative performance metrics. Two key factors informed this selection: (1) the model pre-training on Twitter corpora which optimises its ability to process the lexical and syntactic characteristics of social media short text and informal language, and (2) its demonstrated performance superiority in sentiment classification tasks, outperforming classical approaches (VADER, SVM) and neural architectures (LSTM, biLSTM) as well as BERT-base-cased variants, as established in prior literature [35]. To ensure the validity of our model selection, we performed additional validation by comparing Twitter-roBERTa-base's performance (RoBERTa) against two widely used state-of-the-art fine-tuned models: *distilbert-base-uncased-finetuned-sst-2-english* (DistilBERT) and *nlptown/bert-base-multilingual-uncased-sentiment* (BERT). A subset of 500 randomly selected posts was manually annotated with sentiment labels to serve as ground truth for this comparison. As shown in Table 1, while DistilBERT achieved competitive binary classification performance, its binary classification (positive/negative) was insufficient for our analysis. Consequently, we adopted RoBERTa, which offers three-class sentiment prediction (negative, neutral, positive), a critical requirement for identifying undecided or mixed perspectives on AI.

Model	**Accuracy**	**Macro Precision**	**Macro Recall**	**Macro F1 Score**
RoBERTa	0.74	0.74	0.76	0.75
DistilBERT	0.84	0.85	0.84	0.84
BERT	0.51	0.51	0.55	0.50

Table 1. Performance comparison of sentiment analysis fine-tuned models

3.4. Topic Modelling

This study employed Latent Dirichlet Allocation (LDA) [36] and n-gram modelling [37] to analyse and visualise key topics in social media discussions about AI. LDA uncovered underlying themes in the dataset, treating each document as a mixture of topics and each topic as a distribution over words. The optimal number of topics (k=12) was determined through coherence score evaluation, balancing topic distinctiveness and interpretability. All generated topics underwent manual review by two researchers to ensure coherence and relevance to AI discourse, with discrepancies resolved through discussion. N-gram modelling identified common phrases and contextual patterns, focusing on unigrams, bigrams, and trigrams. This complemented LDA by providing additional context and revealing AI-specific terminology. Additionally, word co-occurrence mapping [38] was employed to further understand the relationships between terms in the corpus, visualising how concepts like "ethics," "regulation," and "job automation" clustered together in discussions.

3.5. Temporal Analysis

Time series analysis techniques were used to examine the temporal dynamics of sentiment and opinion towards AI. The collected data were aggregated at various temporal granularities (daily, weekly, monthly), and change-point detection [39] was applied to identify significant shifts in sentiment over time. In addition, to provide context for observed sentiment shifts, we mapped key AI-related events against our temporal data, including major product releases (e.g., ChatGPT's launch in November 2022), significant research publications, and AI-related news events. This contextual mapping allowed for identifying potential causal relationships between real-world events and public sentiment fluctuations. Finally, time series visualisation

[1] https://huggingface.co/cardiffnlp/twitter-roberta-base-sentiment-latest

methods, such as line plots and heatmaps, were used to present the temporal patterns and trends. Although geographic metadata was initially used, where available, to analyse regional sentiment variations, this dimension was ultimately excluded from our study due to insufficient data coverage—only 23% of Twitter posts contained geolocation information, with even lower percentages on other platforms.

3.6. Reproducibility

To ensure reproducibility of our findings, all code used for data collection, preprocessing, sentiment analysis, and visualisation has been made available in a public GitHub repository [URL to be added upon publication]. The repository includes detailed documentation for each analytical step, requirement specifications, and example notebooks. While raw social media data cannot be shared due to platform terms of service, our repository includes anonymised feature vectors and aggregated results that enable verification of our findings while respecting user privacy.

4. Results & Findings

4.1. Exploratory Data Analysis (EDA)

This study analysed a comprehensive dataset comprising 133,604 entries collected from three major social media platforms: Reddit, YouTube, and Twitter. These entries were merged to form a single data frame for analysis. After pre-processing, the total number of comments subjected to sentiment analysis was calculated as 133,004, as shown in Table 1.

Platform	Number of Comments/Posts/Tweets
YouTube	89,662
Reddit	37,806
Twitter	5,536
Total	**133,004**

Table 2. Distribution of collected posts from social media platforms.

4.2. Sentiment Classification

Sentiment analysis was conducted using the RoBERTa'S *cardiffnlp/twitter-roberta-base-sentiment* model [33, 34] on 133,004 comments, revealing a nuanced of public sentiment towards AI, categorised into negative, neutral, and positive, as shown in Figure 3.

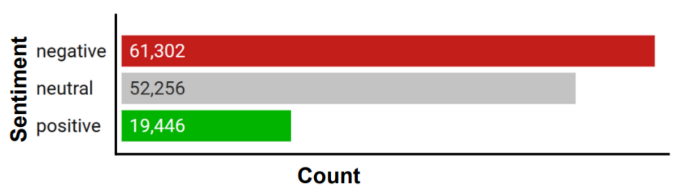

Figure 3. Sentiment distribution in the collected social media posts on AI.

The sentiment analysis revealed a distinct distribution of sentiments across 133,004 entries. Negative sentiment dominated the dataset, accounting for 61,302 entries (46.09%), followed by neutral sentiment with 52,256 entries (39.29%), while positive sentiment comprised the minor portion with 19,446 entries (14.62%). This distribution indicates a significant prevalence of negative sentiment, with nearly half of the analysed content falling into this category. The lexical analysis of sentiment-categorised word frequencies provides a deeper understanding of the discourse surrounding AI technologies, as illustrated in Figures 7 and 8 in Appendix A, which represent positive, neutral and negative comments, respectively. In Figure 4, the most frequent positive terms — *"like"* (3,682), *"good"* (3,232), and *"great"* (2,401) which indicate a substantial level of user satisfaction and approval. However, this is counterbalanced by the prevalence of negative terms, as shown in Figure 5, such as *"bad"* (3,507) and *"problem"* (3,470), suggesting significant user frustration or concern. On the other hand, the neutral category were dominated by *"ai"* (46,420), which underscore the centrality of artificial intelligence in discussions, while terms like *"human"* (8,927) and *"people"* (8,331) point to ongoing comparisons between AI and human capabilities. The presence of *"intelligence"* (1,140) among positive terms and *"dangerous"* (2,273) among negative terms highlights the dual perception of AI as both a promising cognitive tool and a potential threat. This is further emphasised by the coexistence of terms like *"better"* (1,900) and *"work"* (1,596) with *"fear"* (1,960) and *"evil"* (1,432), reflecting a tension between practical benefits and more profound societal anxieties. The high frequency of modal verbs such as *"would"* (9,346) and *"could"* (5,646) in the neutral category indicates a significant amount of speculative discourse surrounding AI's potential applications and impacts. Notably, the slightly higher frequencies of top negative words compared to positive words align with the earlier sentiment analysis, suggesting a marginally more critical overall stance towards AI technologies.

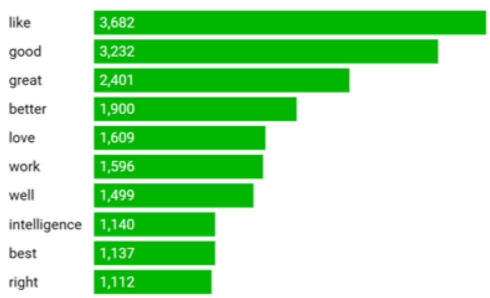

Figure 4. Top 10 most frequent positive terms in the collected social media posts.

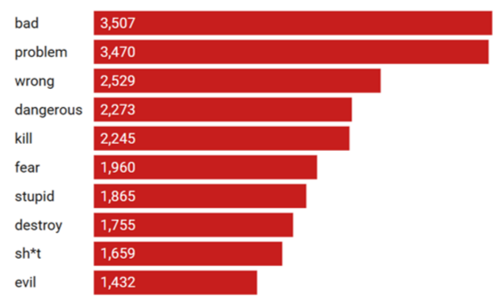

Figure 5. Top 10 most frequent negative terms in the collected social media posts.

4.3. Topic Modelling

Bigrams and Trigrams Found in Corpus: To understand common terms in AI-related discussions, n-gram frequencies (bigrams and trigrams) were analysed. As illustrated in Table 3, the high frequency of *"artificial intelligence"* (2,959) as the top bigram reinforces the corpus's focus on AI as a complete concept rather than just the abbreviation. The prevalence of phrases like *"dont know"* (2,023) and *"dont think"* (1,740) indicates a significant degree of uncertainty or scepticism within the discourse. Interestingly, *"climate change"* (1,472) appears as a high-frequency bigram, indicating a notable connection between AI discussions and environmental concerns. The bigrams *"use ai"* (1,616) and *"ai would"* (1,574) suggest frequent discussions about the applications and potential impacts of AI technology. Among trigrams, *"self driving cars"* (225), suggests that autonomous vehicles are a prominent example used in AI-related discourse, possibly due to their tangible and relatable nature for many individuals. And *"Universal basic income"* (203) appears also as a high-frequency trigram, suggesting a strong connection between AI discussions and economic policy considerations. As for the trigram *"large language models"* (197), it points to discussions about specific AI technologies likely in the context of natural language processing and generative AI systems like GPT (Generative Pre-trained Transformer) models. As for the co-occurrence data, illustrated in Figure 9 (Appendix B), the tokens *"ai > cant > wait"* and *"ai > cant > even > though"* suggest a dichotomy in public sentiment towards AI. The former indicates anticipation and excitement about AI's potential, while the latter implies scepticism or frustration with its current limitations. The prevalence of patterns like *"many > people > dont > know > ai"*, *"many > people > need > know > ai"*, and *"many > people > dont > understand"* highlights a perceived knowledge gap in public understanding of AI. Interestingly, the pattern *"many > people > dont > care"* introduces another dimension to this discourse, suggesting that alongside uncertainty, there may be a segment of the population that is disengaged from AI-related issues. The co-occurrences *"ai > like > human > intelligence"*, *"ai > human > brain"*, and *"ai > human > beings"* reveal a strong tendency to draw comparisons between AI and human cognitive abilities. Phrases like *"look > like > ai"* and *"feel > like > ai"* suggest that discussions often involve attempts to identify or characterise AI, potentially indicating public interest in understanding how AI manifests in everyday experiences. The

Bigram	Frequency	Trigram	Frequency
artificial intelligence	2959	self driving cars	225
dont know	2023	artificial intelligence ai	219
gon na	1885	universal basic income	203
dont think	1740	large language models	197
use ai	1616	dont even know	190
ai would	1574	artificial intelligent entities	173
ai ai	1479	ai gon na	161
climate change	1472	ai machinelearning datascience	160
years ago	1374	machinelearning datascience artificialintelligence	160
think ai	1301	datascience artificialintelligence trending	160

Table 3. Distribution of Bigrams and Trigrams in corpus

patterns *"kill > us > ai"* and *"ai > problem"* point to concerns about potential negative impacts of AI, including existential threats. Simultaneously, phrases like *"ai > help > us"*, *"good > become > ai"*, and *"help > ai"* suggest recognition of AI's potential benefits. The co-occurrence *"ai > replace"* likely refers to concerns about AI replacing human jobs or roles, a theme that emerged strongly in the LDA topic modelling analysis. References to specific AI technologies and concepts, such as *"chat > gpt"*, *"generative > ai"*, *"self > driving"*, and *"machine > learning"*, support the earlier findings on public engagement with technical AI aspects. The co-occurrence *"turing > test"* is particularly noteworthy, as it indicates that some discussions reference historical concepts in AI development. The presence of *"art > ai"* in the co-occurrences reflects the growing discourse around AI's role in creative fields.

Latent Dirichlet Allocation (LDA) Topic Modelling: LDA topic modelling was conducted to to uncover thematic structures in the corpus, revealing 20 topics summarised in Table 4 (Appendix C) with associated keywords. The analysis highlights the diverse and multifaceted themes in AI-related discussions. One notable theme centres on **AI and Spiritual/Philosophical Concepts** (Topic 1), where keywords like *"god," "life," "evil,"* and *"spirit"* reveal an intersection between technology and existential questions. This theme emphasises how AI challenges fundamental beliefs about humanity, consciousness, and ethics. Another prominent theme explores the **Scientific and Technical Aspects of AI** (Topic 2), characterised by keywords such as *"energy," "brain," "cells,"* and *"theory."* This reflects interest in AI's underlying mechanisms, including neural networks, energy efficiency, and its interplay with fields like neuroscience and physics. The societal impacts of AI also feature prominently. **AI's Impact on Jobs and Creative Industries** (Topic 12) highlights concerns about AI transforming the labour market, especially in creative fields, with keywords like *"jobs," "replace," "artists,"* and *"music."* Similarly, **AI in Business, Economy, and Job Market** (Topic 13) extends this discussion to broader economic implications, focusing on keywords such as *"companies," "money," "market,"* and *"cost"*. Ethical considerations emerge as a critical theme in **AI Ethics, Safety, and Development** (Topic 8), with keywords like *"safety," "ethical," "bias,"* and *"concerns."* This highlights the importance of responsible AI development, addressing risks, transparency, and fairness.

4.4. Sentiment Trends (2017-2024)

Analysing sentiment trends over the years reveals significant shifts in public perception of AI, offering valuable insights into how attitudes have evolved in response to technological advancements, societal changes, and emerging challenges. The period from 2017 to 2018 (Figure 6) is characterised by high sentiment volatility, with sharp fluctuations between negative, neutral, and positive sentiments. January 2017 started with an overwhelmingly neutral sentiment, with nearly 100% of comments classified as neutral. This initial neutrality might reflect a lack of strong opinions about AI at the time, possibly due to limited public awareness or understanding of the technology. However, this neutral stance quickly gave way to predominantly negative sentiments for most of 2017 and 2018. Moving into 2019-2020 (Figure 10 - Appendix D), we observe a stabilisation of sentiment trends, with negative sentiment consistently dominating, followed by neutral and then positive. This period shows less volatility than the previous two years, suggesting a consolidation of public opinion regarding AI. Negative sentiment often exceeded 50% of comments throughout this period,

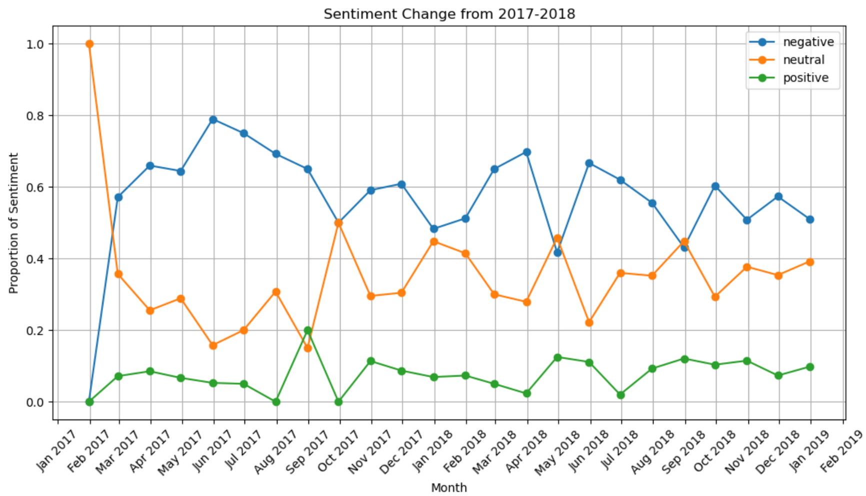

Figure 6. Temporal Sentiment Analysis between 2017-2018

indicating a predominantly cautious or concerned attitude towards AI While consistently lower than negative sentiment, neutral sentiment remained significant throughout this period. This suggests that most discourse maintained a balanced or undecided stance on AI issues. The period of 2021-2022 (Figure 11 - Appendix D) shows a slight moderation in negative sentiment, though it remains the dominant sentiment category. During that period, notable spikes in neutral sentiment occurred, particularly in May 2022, when it briefly surpassed negative sentiment. In the most recent phase, 2023-2024 (Figure 12 - Appendix D), AI sentiment trends show significant developments. Negative sentiment remains dominant, but neutral sentiment has increased, often matching or nearing negative levels, suggesting an evolving public perception as AI becomes more integrated into society. Positive sentiment, while still the lowest category, shows slight increases in early 2024, indicating a gradual shift in discourse.

5. Discussion: Limitations and Delimitations

This study has several limitations that should be considered. First, the accuracy of sentiment analysis may be compromised by linguistic nuances such as sarcasm, irony, and ambiguous language, which automated tools often struggle to interpret. Second, the demographics of users on the examined platforms (Twitter, YouTube, and Reddit) may not be fully representative, potentially limiting the generalisability of findings to broader populations. Third, the analysis is confined to English-language content, excluding non-English perspectives. Finally, the fixed timeframe for data collection may not capture evolving sentiment trends over longer periods. In terms of delimitations, this study intentionally focuses on publicly available posts discussing general AI rather than specific applications, ensuring a consistent scope. Additionally, bot-generated content was excluded to enhance the reliability of human-driven sentiment analysis. These boundaries were established to maintain methodological coherence while clearly defining the study's focus.

6. Conclusion

Sentiment analysis of AI-related social media discourse reveals predominantly negative yet nuanced public perceptions, with significant neutral sentiment, reflecting both concerns and knowledge gaps. Topic modelling identified diverse themes—from technical details to philosophical debates—indicating sophisticated public engagement. Temporal trends revealed growing discussions and evolving sentiments, reflecting a more nuanced understanding of AI over time. Key findings highlight widespread economic and ethical concerns, rising interest in AI's societal impacts, and the need for balanced perspectives. To address these challenges, the study recommends comprehensive education, ethical guidelines, transparent communication, and balanced media coverage to bridge knowledge gaps and cultivate informed public discourse on AI.

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Appendix A: Word cloud and top ten most frequent terms

Figure 7. Word cloud (left) and list of top 10 (right) most frequent positive words in the corpus.

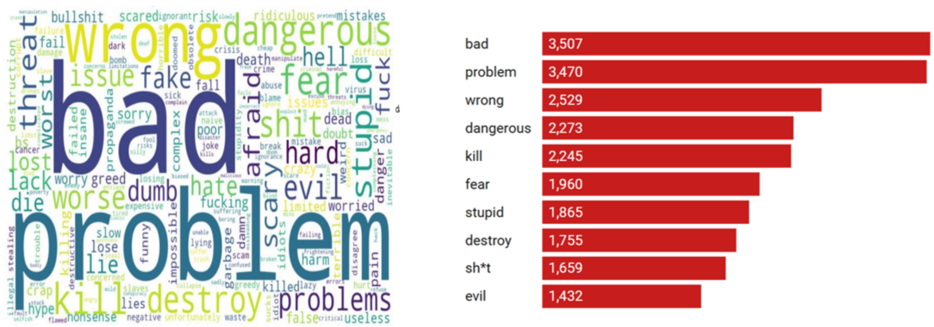

Figure 8. Word cloud (left) and list of top 10 (right) most frequent negative words in the corpus.

Appendix B: Bigram distribution with over 100 interactions

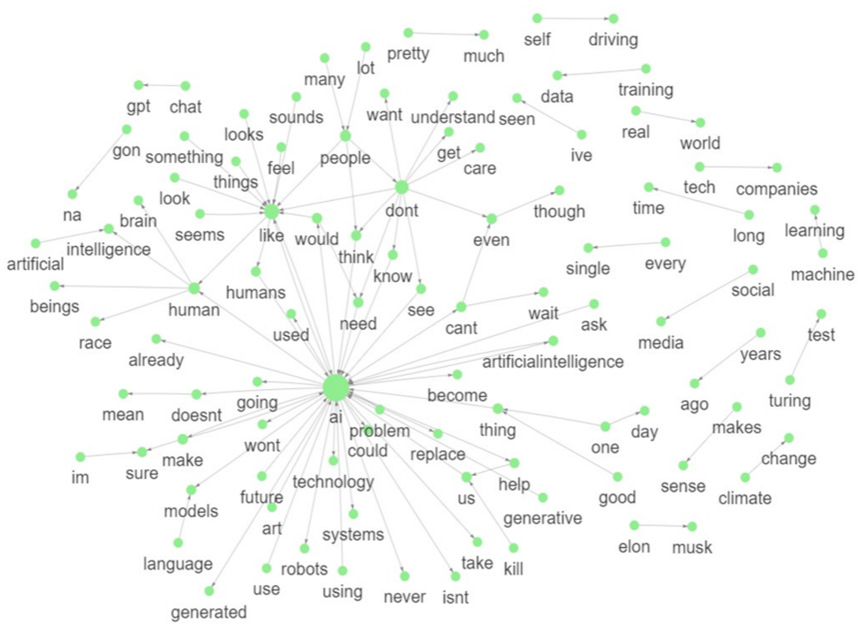

Figure 9. Direction of bigrams with over 100 interactions in the corpus represented in the form of graph.

Appendix C: LDA Topic Distribution

Topic	Discovered Theme(s)	Keywords
0	General AI Technology and Applications	ai, artificialintelligence, technology, chatgpt, machinelearning, future, potential, tech, artificial intelligence, amp, generative, new, datascience, midjourney, robotics, art, via, ml, using
1	AI and Spiritual/Philosophical Concepts	god, ai, people, life, like, jesus, us, know, one, love, believe, world, evil, created, gods, man, dont, christ, beast, spirit
2	Scientific and Technical Aspects of AI	could, energy, data, would, brain, also, new, research, system, power, space, make, one, cells, process, systems, great, theory, used, light
3	AI, Human Emotions, and Future Speculation	ai, man, future, good, fear, love, afraid, great, world, one, said, quot, guy, mo, like, thank, day, end, come, podcast
4	AI in Media and Software Development	ai, video, wait, years, hes, cant, said, great, real, ago, thank, well, oh, software, thanks, future, like, made, till, good
5	Advanced AI Systems and Language Models	data, intelligence, ai, models, model, learning, agi, like, training, machine, gpt, artificial, llms, language, think, even, human, current, based, much
6	AI and Human Consciousness	ai, human, humans, would, intelligence, us, consciousness, intelligent, like, could, think, even, never, may, way, become, life, conscious, emotions, artificial
7	AI in Internet and Search Technology	like, google, people, ai, internet, time, search, dont, get, use, one, also, much, even, see, youtube, think, tech, want, still
8	AI Ethics, Safety, and Development	ai, like, ais, need, safety, ethical, use, development, systems, data, tool, public, open, used, potential, bias, human, concerns, also, good
9	AI in Media, Marketing, and Customer Service	media, social, new, ai, read, job, paid, news, get, technology, service, youre, dont, customer, claims, content, click, fair, marketing, articles
10	AI's Impact on Humanity and Climate	ai, humans, us, human, humanity, world, control, technology, like, change, life, one, would, already, robots, way, climate, could, power, time
11	AI Skepticism and Human-AI Comparison	ai, dont, know, even, people, think, would, like, make, human, say, thats, things, really, one, something, doesnt, actually, art, real
12	AI's Impact on Jobs and Creative Industries	ai, jobs, people, job, work, going, replace, get, music, replaced, years, make, new, artists, got, like, take, art, one, already
13	AI in Business, Economy, and Job Market	ai, companies, money, people, tech, work, company, would, need, cost, market, pay, jobs, make, less, years, use, much, even, time
14	AI in Education, Law, and Copyright	use, data, school, like, one, would, law, copyright, also, case, kids, students, get, well, fair, used, something, article, way, legal
15	AI in Transportation and Energy	would, like, get, dont, car, water, go, cars, air, need, even, one, thats, cant, said, still, going, make, power, could
16	AI in Entertainment and Robotics	ai, like, robot, people, want, voice, movie, sounds, get, right, lol, ask, watch, dont, think, bad, movies, see, hear, hearing

17	AI's Potential Impact and Human Concerns	ai, us, people, dont, think, world, going, need, good, want, would, make, get, humans, like, stop, know, take, kill, way
18	Practical Applications of AI in Computing	use, chatgpt, ai, email, windows, code, dont, gmail, google, computer, using, app, emails, coding, programming, python, software, good, apple, linux
19	User Experiences with AI (especially ChatGPT)	like, would, said, chatgpt, one, time, good, didnt, get, could, really, something, feel, asked, gpt, person, used, people, way, even

Table 4. Extracted topics and their associated themes and Keywords

Appendix D: Temporal Sentiment Analysis

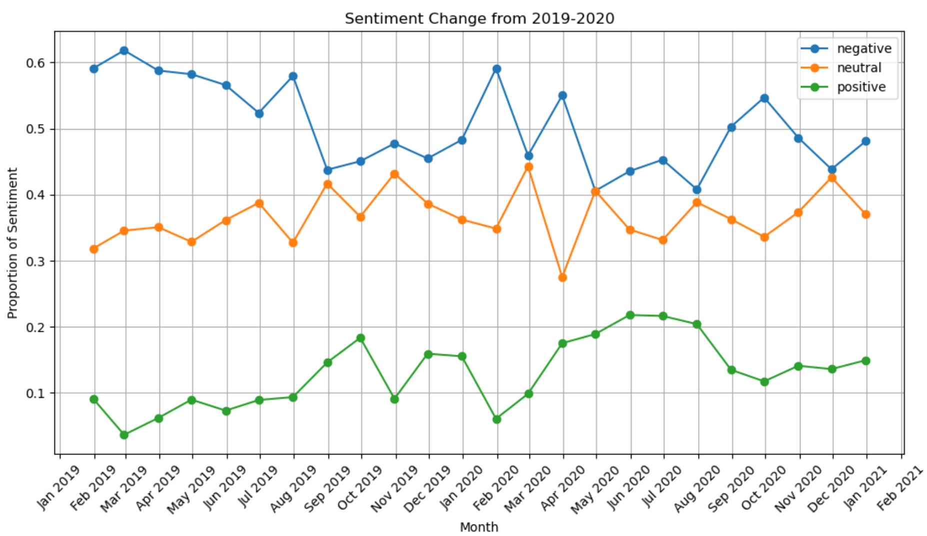

Figure 10. Temporal Sentiment Analysis between 2019-2020

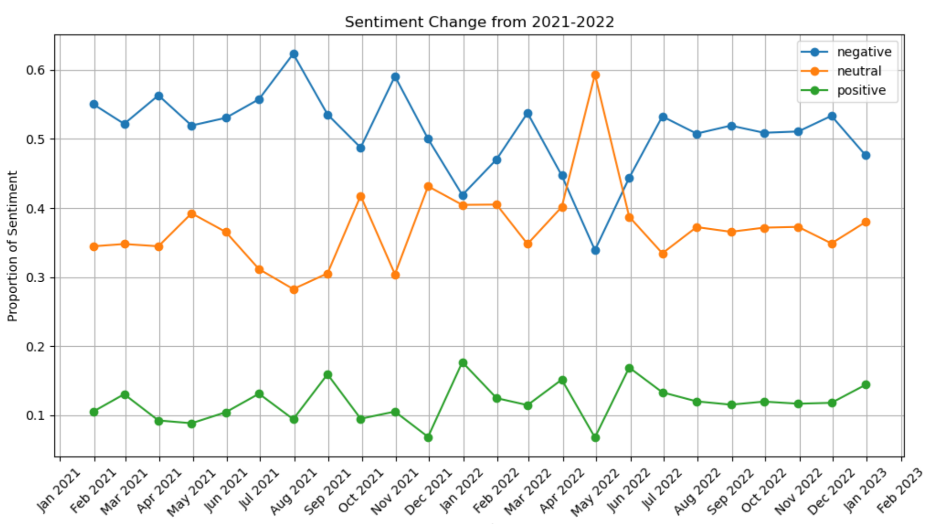

Figure 11. Temporal Sentiment Analysis between 2021-2022

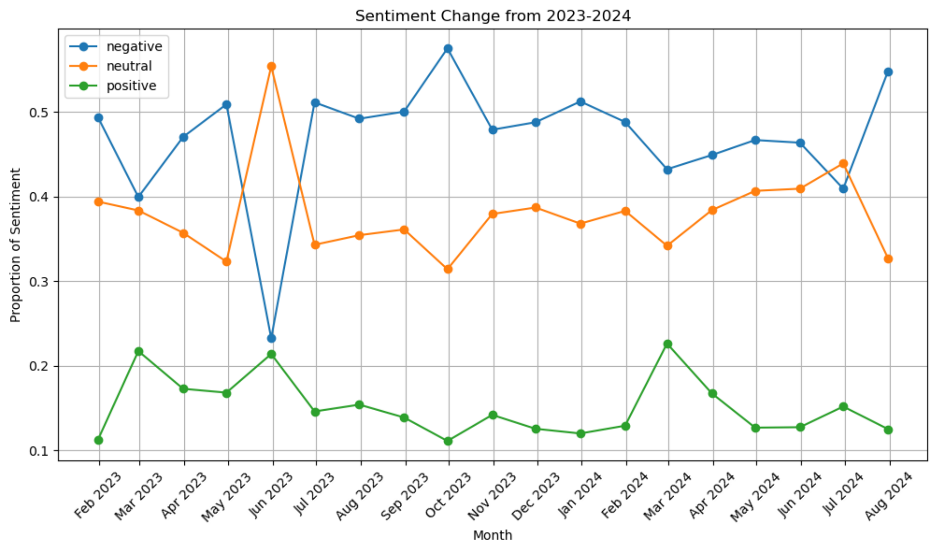

Figure 12. Temporal Sentiment Analysis between 2023-2024