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HIDDEN GREENS – AI'S ROLE IN SUSTAINABILITY THROUGH OPINION MINING

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ABSTRACT: This research explores the intersection of artificial intelligence (AI) and sustainability discourse, primarily focusing on public opinion expressed on the Reddit platform. Using unsupervised machine learning and large language models (LLMs), we conduct opinion mining and sentiment analysis on a diverse range of Reddit discussions related to sustainability, employing both fine-grained analysis and traditional statistical methods like bigram and frequency analysis. Our findings reveal key trends in public perception and evolving attitudes towards sustainability, highlighting areas of concern and potential opportunities for intervention. Additionally, we demonstrate how AI can significantly expedite model development, enabling rapid responses to shifts in public opinion. This agility is crucial for aligning sustainability initiatives with the values and concerns of diverse stakeholders. While acknowledging the limitations of Reddit as a representative sample of global opinion and the need for further validation of AI's capabilities in specific sustainability contexts, this study provides valuable insights into the dynamic relationship between AI and sustainability discourse. By understanding public sentiment and leveraging AI's potential for rapid adaptation and analysis, we can inform more effective strategies for addressing environmental challenges and promoting a sustainable future.

KEYWORDS: artificial intelligence, sustainability, opinion mining, sentiment analysis, Flan T5 XL, Gemma 9 B it

Introduction

The urgency of addressing global sustainability challenges has intensified due to escalating environmental crises and societal demand for action. As nations and corporations strive to meet the United Nations' Sustainable Development Goals (SDGs) set in 2015 (United Nations, 2015), Artificial Intelligence (AI) has emerged as a pivotal tool in facilitating these efforts. AI's ability to quickly analyse large datasets is critical for understanding public sentiment and adapting strategies in real-time to align with evolving environmental and social priorities (Haleem et al., 2022; Vinuesa et al., 2020). From 2021 to 2023, there has been a surge in public engagement with sustainability topics on social media platforms, presenting an opportune moment to study AI's role in shaping public discourse.

This study explores the intersection of AI and sustainability within the context of public opinion mining, focusing on Reddit discussions that capture a wide range of global perspectives. Utilising advanced AI tools for opinion mining and sentiment analysis, we extracted insights from extensive unstructured text data. By systematically harvesting discussions from various sustainability-related subreddits using the Python Reddit API, we concentrated on posts about climate change, renewable energy, and ecological conservation. This approach provided a comprehensive understanding of public sentiment, using two stand-alone LLMs, Flan T5 XL and Gemma 2 9B it (instruction trained), and how it evolved over time.

Our analyses reveal a complex landscape of opinions, ranging from strong advocacy for green policies to scepticism about their impacts. Employing language models specifically trained for sentiment analysis, we categorised post sentiments into positive, negative, and neutral. This classification quantifies community perceptions of sustainability initiatives and highlights significant shifts in public opinion.

The results underscore AI's potential as a crucial tool for understanding and navigating public opinions on sustainability. Mapping sentiment trends offers valuable insights for policymakers, business leaders, and environmental advocates regarding public attitudes toward sustainability efforts. In summary, this paper enhances our understanding of AI's capacity to analyse public sentiment and sheds light on the broader implications for promoting a sustainable future. The following sections detail the methodologies employed, discuss the findings, and explore potential pathways for integrating AI into sustainable practices informed by public opinion.

Literature Overview

Artificial intelligence technology has increasingly become a part of everyday life for many people and businesses. The launch of ChatGPT, a large language model by OpenAI, captivated the public and quickly gained widespread recognition, becoming a significant breakthrough in AI-driven communication technologies (Heaven, 2023). However, AI is more than just text-based LLMs that answer simple prompts. It has the potential to drastically reshape, optimise, and boost the productivity of many sectors, industries, and businesses, perhaps even being the most disruptive force in the 21st century, according to Jorzik et al. (2024). This paper, in particular, explores the intersection of AI and sustainability.

As we collectively recognise the need for more sustainable business models, solutions, and technology due to growing global environmental challenges such as climate change, resource depletion, and biodiversity loss, AI's role in sustainability has become a focal point in both academic and practical discourse (Haleem et al., 2022; Vinuesa et al., 2020). AI-powered solutions not only enhance efficiency but also enable more informed, data-driven decisions that, according to Schoormann et al. (2023), can help achieve several of the UN's Sustainable Development Goals ~such as healthy lives (SDG 3), quality education (SDG 4), smart and safe communities (SDG 9), and modern energy (SDG 7). Moreover, AI can generally reduce environmental footprints (Das, 2021).

Taking the SDGs as an outline of what constitutes sustainability, 191 countries have signed on to achieve these goals, making them a globally recognised framework for sustainable development (United Nations, 2015). This widespread adoption emphasises the relevance of addressing critical issues such as climate change, biodiversity loss, and social inequality. Current research identifies the most crucial intersections of AI and sustainability with high potential for synergies (Schoormann et

al., 2023; Vinuesa et al., 2020). However, it is essential to note that these are only key areas and examples of notable AI solutions for each topic and do not represent all possible synergies in depth.

Current Critical Topics in AI and Sustainability

1 Climate Change and Global Warming

Climate change refers to the long-term alteration of temperature and weather patterns, which scientists widely believe is primarily caused by human activities, especially the production of CO₂ through the burning of fossil fuels. These emissions trap heat in the Earth's atmosphere, leading to global warming and associated climate disruptions. If not addressed, climate change could severely impact ecosystems, human health, and global economies. Therefore, addressing CO₂ emissions is central to climate action, mitigation, and sustainability efforts (Yoro & Daramola, 2020).

AI technologies enable more accurate climate modelling, helping policymakers and industries predict and respond to the impacts of climate change (Vinuesa et al., 2020). As climate change rapidly and sometimes unpredictably affects the environment, artificial intelligence significantly enhances weather forecasting by processing large volumes of satellite and meteorological data, leading to more accurate temperature, precipitation, and wind speed predictions. Machine learning algorithms and deep learning models improve prediction precision, reduce bias, and increase the timeliness of forecasts, ultimately helping mitigate weather disasters and optimise land use efficiency (Chen et al., 2023).

2 Energy Efficiency and Renewable Energy

The growing global demand for energy, driven by population growth and urbanisation, has led to the widespread use of non-renewable energy sources, causing adverse environmental effects such as climate change and global warming (Bennagi et al., 2024). In line with the need for clean and affordable energy, the integration of renewable energy sources and improving the efficiency of current energy systems are at the forefront of sustainability efforts (Bennagi et al., 2024).

AI has transformed the renewable energy sector by optimising infrastructure maintenance, improving energy generation, and integrating renewable sources into existing grids. Through predictive maintenance and advanced forecasting models, AI minimises downtime, enhances efficiency, and helps balance the intermittent nature of renewable energy sources like solar and wind (Hamdan et al., 2024).

Moreover, AI is advancing energy management systems by integrating Internet of Things (IoT) technologies, allowing for more granular control and monitoring of energy use (Das, 2022). This tighter oversight and predictive interconnectivity can help reduce the waste of non-renewable resources and increase the integration and efficiency of renewable energy systems. Additionally, AI-driven demand response systems enable real-time adjustments to energy consumption, helping balance supply and demand and further optimising the use of renewables. This results in a more resilient energy grid that adapts dynamically to fluctuations in renewable energy generation, improving overall sustainability (Khalid, 2024).

One example of AI-based energy efficiency is in the transportation sector, which currently contributes to nearly one-third of total global emissions. By optimising routes, improving fleet management, enabling autonomous vehicles, and enhancing public transit systems, AI integration can help lower emissions and increase overall efficiency (Chen et al., 2023).

3 Environmental Monitoring and Conservation

Climate change and global warming inevitably affect the environment and its inhabitants, including fauna and flora. As animal species face ecosystem shifts, rising temperatures, and altered weather patterns, they must adapt, migrate, or risk extinction, disrupting the natural balance of biodiversity (Muluneh, 2021). Flora is similarly affected by shifting temperatures and altered rainfall patterns, impacting growth cycles, reproduction, and distribution (Muluneh, 2021). Many plant species cannot adapt quickly enough, leading to a decline in biodiversity and further disruption of ecosystems. This

also affects agriculture, as essential crops may become less productive or fail altogether in regions where they once thrived (Muluneh, 2021; Myers et al., 2017).

AI's capability to predict climate change patterns is helpful in biodiversity management and conservation, as it helps identify at-risk areas (Shivaprakas et al., 2022). AI can synthesise large quantities of data from multiple sources, such as camera traps, drones, GPS, IoT, and environmental DNA, to predict and track deforestation trends or natural disasters (fires, pests, and storms). It also monitors wildlife, assesses habitat health, maps forests, tracks carbon and timber resources, and manages inventories, enabling conservationists to make real-time, informed decisions for ecosystem restoration and forest health monitoring (Garske et al., 2021; Wandg et al., 2025).

4 Environmental, Social, and Governance (ESG)

Environmental, Social, and Governance (ESG) encompasses a broad spectrum of topics related to sustainable development within organisations, focusing on their economic, environmental, and societal impacts (Senadheera et al., 2022). The concept originated from discussions around socially responsible investment (SRI) in the 1960s and has since evolved into a framework used to measure a company's performance in three key areas: the environment, society, and governance. The importance of ESG was further supported by the creation of the UN's SDGs and the global acknowledgement of the climate crisis.

ESG also emphasises measurable criteria, making it a key factor for investors and stakeholders when evaluating the sustainability and long-term strategic decisions of companies, as companies with ESG practices tend to have overall better performance, with higher returns and more stable portfolios (Senadheera et al., 2022; Burnaev et al., 2023).

AI plays a crucial role in addressing ESG challenges by offering solutions for improving environmental management, enhancing social responsibility, and strengthening governance practices. AI can monitor labour conditions and supply chain practices, ensuring companies adhere to ethical standards. Additionally, AI enhances transparency and compliance by processing ESG reports, identifying key metrics, and assessing ESG risks (Burnaev et al., 2023).

Criticism of AI use

Despite its transformative potential, AI, like any technology, faces criticism around its use, primarily when it comes to sustainability and the need for fair application. It is therefore important to mention the currently discussed issues as the ethical use of AI is related to its sustainability.

Firstly, the training and learning process of large AI models, which is a key step in creating a functional AI model, requires enormous computational power and energy. Naturally, this leads to high electricity consumption and subsequent high carbon emissions. In addition, these models generate a significant amount of heat during operation, and the servers running these models must be continuously cooled, primarily with water. Thus, it is important to find a balance of sustainability, as these models demand large resources and have an unsustainable environmental impact (Gupta, 2024; van Wynsberghe, 2021; Wu et al., 2021).

Secondly, the performance of AI critically depends on the quality of the data it learns from, as each model is only as good as the quality of the data upon which it is built and trained. Incomplete, outdated, or biased data can lead to ineffective results and may unintentionally replicate existing prejudices and stereotypes (Lee et al., 2024; Galaz et al., 2023).

Moreover, ethical concerns and privacy issues also arise from the general use of AI in processing and manipulating sensitive or personal data. AI's ability to collect and process vast amounts of personal information naturally raises concerns about how such data is used, stored, and protected. For example, the absence of regulations governing the ethical use of AI in areas such as financial modelling and resource allocation creates the potential for abuse or misuse (Lee et al., 2024).

Thirdly, the concentration of AI development within a few dominant corporations or states poses a risk of monopolisation and geopolitical dominance, which further challenges the concept of global fair access (Tripathi et al., 2024).

And last but not least, while AI can significantly enhance data-driven sustainability efforts, it also plays a role in spreading misinformation on environmental topics. Social media platforms, in particular, have proven to be effective vehicles for disseminating climate change misinformation (van der Ven et al., 2024). Advances in natural language processing and image generation now make it easier than ever to produce realistic fake articles, social media posts, or even deepfake videos that quickly propagate false sustainability narratives with minimal resources.

Despite these challenges, AI remains a powerful tool in the fight against misinformation due to its ability to identify hidden patterns in large datasets. For example, AI can be employed to detect and flag bot-created content or posts based on misinformation (Kertysova, 2018). Ultimately, while AI—like any technology—has its drawbacks, its responsible and credible use is essential in both mitigating misinformation and harnessing its potential for promoting genuine sustainability efforts.

Research Gap

Despite the stellar examples of AI aiding sustainability efforts, it is important to note the research gap this paper seeks to address. Many of the cited papers have established AI's potential to aid sustainability efforts, particularly the SDGs. However, this paper aims to address a less-researched area: real-time assessment of AI implementation in sustainability, particularly through public opinion.

Public opinion is crucial since sustainability-related issues are global, as indicated by the commitment of 191 countries (United Nations, 2015). As AI is used to optimise efficiency and productivity across all societal levels, it is important to consider the ethics of its use (Stahl, 2021). Therefore, if AI is to benefit all people, they should have an equal say in how it is used, along with the organisations and companies that implement it.

Sentiment Analysis and Its Role in AI and Sustainability

Given AI's capabilities, what better way to deploy it than to assess its own implementation? Social interactions on the internet, particularly on social media, cover various topics and provide a pool of public sentiment for research analysis (Naseem et al., 2021).

Sentiment analysis, also known as opinion mining, is a subfield of NLP that focuses on extracting and classifying sentiments expressed in text. By analysing user-generated text, researchers can understand public opinions and attitudes, uncover trends in public discourse, and inform policymakers and businesses about societal attitudes toward chosen issues and AI-driven solutions (Wankhade et al., 2022).

Businesses can utilise sentiment analysis to improve their sustainability practices by identifying consumer preferences and responding to market demands.

In conclusion, this paper will explore the sentiment of public opinions on AI's role in sustainability, highlighting both its potential benefits and ethical concerns. Understanding these sentiments is crucial for guiding responsible AI implementation in addressing global challenges. Further research in this area can inform sustainable development policies and practices.

Methodology

This research systematically analyses public opinion on AI solutions in the context of sustainability through sentiment analysis of text data collected from Reddit. The following sections detail the data collection, cleaning, sentiment analysis, and evaluation processes used to address the **research question**: What are societal attitudes toward AI solutions in selected areas of sustainability?

Data Source and Rationale

Reddit was chosen as the primary data source due to several technical and practical advantages that align well with the study's objectives. From a technical perspective, Reddit's API offers straight-

forward access to comprehensive data, including full discussion threads, user comments, timestamps, upvotes, and other metadata, which are essential for detailed sentiment analysis and opinion mining.

In contrast, platforms like Twitter, where high-resolution historical data often comes at a significant cost, and Facebook or Instagram, where API restrictions limit access to in-depth discussions, Reddit provides an open, cost-efficient repository of user-generated content. Its subforum structure, or “subreddits,” enables focused discussions on specific topics, including AI and sustainability.

This makes the methodology, specifically the use of Reddit as a data source, easily accessible, transparent, replicable, verifiable, cost efficient and accessible even to smaller institutions and researchers. Therefore, for us, Reddit provides a valuable source for analysing real-time societal attitudes toward complex issues seemingly at no cost.

Previous studies (Brett et al., 2019; Savela et al., 2021) have successfully utilised Reddit for sentiment analysis, highlighting its rich text-based content. Additionally, Proferes et al. (2021) found a concentration of research and data utilisation on Reddit, with many studies using computational textual analysis, including machine learning, natural language processing, and topic modelling. This reinforces the credibility and relevance of Reddit data for this research.

Access to data in this study was facilitated through Reddit’s Application Programming Interface (API), which allows for efficient retrieval of posts, comments, and metadata using Python. The detailed methodology for data collection, preparation, and analysis is outlined below.

Data Collection and Preparation

Data Privacy

Using public Reddit data for research raises important privacy and ethical questions, even though the data is openly accessible. Reddit users operate under pseudonyms, but they may still share personal stories or sensitive opinions (for instance, experiences with climate anxiety or local environmental issues) under the assumption that their audience is the Reddit community, not academic researchers.

Therefore, the data in this research does not include mentions of individual posts, pseudonyms, names of users, personal identification data, and excludes any direct citations of posts to ensure the original individual posts used for this research are not traceable through personal identifications. Despite our choice to take precautions to ensure user anonymity, other researchers argue that content on open forums is “deliberately intended for public consumption”, meaning it’s acceptable to use these posts for research without explicit consent, including all publicly visible data (Reagle, 2022). But of course, this is a subject of its own and not the research focus of this paper.

Reddit API

The data collection process utilised the Reddit API through the Python Reddit API Wrapper (PRAW). APIs enable structured data retrieval, acting as intermediaries between software applications. In this study, PRAW was used to extract posts and comments from various subreddits. The retrieved data included post titles, bodies, scores (indicating popularity), comment counts, flairs, timestamps, and other metadata. Certain details, such as usernames and URLs, were collected but deemed irrelevant for this study’s purpose.

Subreddits

Subreddits were selected based on their relevance to AI, sustainability, and related themes, as well as the size of their databases, to manage computational resources effectively. The complete list of subreddits and their subscriber numbers is shown in Table 1.

Table 1. Subreddits

Subreddits	Subscribers	Subreddits	Subscribers
Alethics	4,403	envirotech	6,275
artificial	893,373	Futurology	20,653,915
ArtificialIntelligence	672,870	golang	269,765
Bard	42,091	GPT3	1,043,812
C_Programming	169,863	LocalLLaMA	205,505
ChatGPT	6,787,690	MachineLearning	2,913,442
ClaudeAI	56,078	matlab	60,089
climate	205,208	OpenAI	1,745,190
ClimateActionPlan	92,763	Python	1,266,417
ClimateOffensive	71,017	Rlanguage	41,694
ControlProblem	19,880	rust	308,254
c++	290,388	singularity	2,976,027
datascience	2,035,687	solarpunk	139,603
deeplearning	163,782	sustainability	719,770
ecology	91,658	ZeroWaste	1,093,972

Source: author's work based on data from Reddit.

Queries

Based on the literature review, relevant queries were chosen to filter posts that align with the key topics in AI and sustainability. The 37 queries used to retrieve the data are listed in Table 2. Lucene query syntax format was used to allow for the use of indefinite forms and extended logic to use of 'AND' connections to capture various permutations of the term, such as using 'AI AND Climat*' to encompass related terms like 'AI AND Climate,' 'AI AND Climatology,' 'AI AND Climatic,' and others.

Table 2. List of queries

List of queries	
"AI" AND "Climat*"	"GPT" AND "Climat*"
"AI" AND "Sustain*"	"GPT" AND "Sustain*"
"AI" AND "Environment*"	"GPT" AND "Environment*"
"AI" AND "carbon"	"GPT" AND "carbon"
"AI" AND "renewable"	"GPT" AND "renewable"
"AI" AND "ecology"	"GPT" AND "ecology"
"AI" AND "energy"	"GPT" AND "energy"
"AI" AND "ESG"	"GPT" AND "SDG"
"AI" AND "SDG"	"GPT" AND "CO2"
"AI" AND "CO2"	"ChatGPT" AND "Climat*"
"OpenAI" AND "Climat*"	"ChatGPT" AND "Sustain*"
"OpenAI" AND "Sustain*"	"ChatGPT" AND "Environment*"
"OpenAI" AND "Environment*"	"ChatGPT" AND "carbon"
"OpenAI" AND "carbon"	"ChatGPT" AND "renewable"

List of queries	
"OpenAI" AND "renewable"	"ChatGPT" AND "ecology"
"OpenAI" AND "ecology"	"ChatGPT" AND "energy"
"OpenAI" AND "energy"	"ChatGPT" AND "SDG"
"OpenAI" AND "SDG"	"ChatGPT" AND "CO2"
"OpenAI" AND "CO2"	

Each post retained the assigned query that retrieved it, serving as a topic differentiation mechanism for the subsequent analysis. Multiple queries retrieved some posts, which did not pose an issue, as each topic was analysed in the context of its corresponding query. Note the use of ChatGPT and OpenAI query, this query selection was made to reflect the general attitude towards generative LLM as a proxy, as they have similar functionality, but the ChatGPT model by OpenAI is the most commonly and widely used model, as highlighted in the literature overview as well as supported by data from OpenAI itself which stated that ChatGPT has 200 million weekly active users, as of August 2024. This is double the number of users it had a little less than a year ago, highlighting its evergrowing use (Fried, 2024).

Data Cleaning

The raw dataset consisted of 8,526 unique posts that required cleaning before analysis. The data cleaning process involved:

- Removing illegal characters (e.g., non-printable ASCII control characters), URLs, and non- alphanumeric symbols using regular expressions.
- Filtering posts based on combined length of title and body, ignoring characters after the limit of 4,096 characters for the Flan T-5 XL LLM, and for Gemma 2 9B it posts that exceed 2,048 characters, and focusing on those containing a minimum number of words with at least four characters for meaningful sentiment extraction.
- Removing posts with missing attributes to maintain dataset consistency.
- Removing basic English stopwords.

By meticulously cleaning the data, we were able to focus on well-formed, contextually rich text data. This, in turn, significantly enhanced the accuracy of our sentiment analysis.

Data Analysis

The core of the data analysis used Python in conjunction with experimental, stand-alone large language models (LLMs) for sentiment analysis, specifically the Flan T5 XL and Gemma 2 9B (instruction tuned) models. The advantage of this approach lies in the stand-alone nature of the LLMs, which ensures data security and reduces resource consumption, including CO₂ emissions, by leveraging already existing pre-trained models and not building ones from scratch. The key strength of these models is their high accuracy described below.

Sentiment Analysis

Various sentiment analysis models exist with differing levels of accuracy. A study by Hartmann et al. (2023) analysed 272 datasets and 12 million sentiment-labeled documents, comparing three commonly used methods: Transfer Learning (TL), Traditional Machine Learning (ML), and Lexicons (LX). The study found:

- TL: Achieved 94% accuracy for two-class classification (positive/negative) using large sample sizes and document-length text, which decreased to 81% for three-class classification (positive/negative/neutral).
- Traditional ML: Methods like support vector machines and random forests showed 93% accuracy for two-class and 81% for three-class classification with large sample sizes and document-length text.

- LX: Despite their interpretability and common use, they performed lower overall, with 72% accuracy for two-class and 60% for three-class classification.

Similarly, Rustam et al. (2021) evaluated five common ML techniques on COVID-19-related tweets, reporting accuracies of 92% for Random Forest (RF) and XGBoost, 89% for Support Vector Classifier (SVC), 93% for Extra Trees Classifier (ETC), and 91% for Decision Tree (DT).

Comparable results utilising similar ML sentiment analysis techniques were found in studies by Naseem et al. (2021), Pandian (2021), Zhang et al. (2024), and Wan Min and Zulkarnain (2020).

Flan T5 XL Accuracy

Flan T5 XL is an open-source LLM that's available for commercial usage and published by Google researchers. It is an encoder-decoder model pre-trained on various language tasks and specially trained to execute promoting tasks such as summary (Longpre et al., 2023).

To test the accuracy of the Flan T5 XL model, we utilised two datasets available at the Hugging-face.co platform that were both previously used as text classification benchmark datasets in the study by Zhang et al. (2015a, 2015b) for Character-level Convolutional Networks for Text Classification. Both datasets contain labelled sets of reviews and are the Yelp reviews polarity dataset, which categorises Yelp reviews into negative (stars 1 and 2) and positive (stars 3 and 4), with a total of 560,000 training samples and 38,000 testing samples, and the Amazon reviews dataset contains approximately 35 million reviews.

The results of the accuracy labelling of the datasets with a sample size of 380 random reviews for each dataset by the Flan T5 XL model can be found in Tables 3 and 4 below.

Table 3. Amazon Review Polarity Flan T-5 XL scores

Amazon Review Polarity Flan T5 XL scores				
	Category	Precision	Recall	F1-Score
0	Negative	0.930481	0.977528	0.953425
1	Positive	0.979275	0.935644	0.956962
Overall	Overall	0.955263		

Table 4. YELP Review Polarity Flan T5 XL scores

YELP Review Polarity Flan T5 XL scores				
	Category	Precision	Recall	F1-Score
0	Negative	0.968421	0.989247	0.978723
1	Positive	0.989474	0.969072	0.979167
Overall	Overall	0.978947		

Table 3 shows the accuracy of two-class sentiment labelling at 95 % for the Amazon Review Polarity dataset, and Table 4 shows 98 % accuracy for the YELP Review Polarity dataset.

An example of prompt engineering used when testing the Flan T5 XL model can be found below: T5 Zero Shot prompt: ""

Please perform Sentiment Classification task. Given the sentence, assign a sentiment label from ['negative', 'positive']. Return the label only without any other text. ""

Gemma 2 9B it.

The Gemma 2 9B it LLM model, also a state-of-the-art open model from Google, was built from the same research and technology used to create the Gemini models. It is also a text-to-text, decoder-only LLM. The accuracy of this model for specific sentiment analysis has not yet been published, but it has a recorded high level of accuracy due to its advanced training methodology, such as knowledge distillation. The 9B model, in particular, shows "massive improvement" compared to previous versions, with performance results that are competitive even against models 2-3 times larger (Google Team &

Google DeepMind, 2024). However, its smaller sister model, Gemma 7B, has an accuracy of 93% for sentiment analysis (Mo et al., 2024).

Therefore, the Gemma 2 9B it was used as a comparison model to validate the Flan T-5 XL model's performance. But to further validate this claim, we tested the Gemma 2 9B model on the same datasets as the Flan T5 XL, with the results of a random sample of 512 reviews for each dataset set respectively in Tables 5 and 6 below.

Table 5. Amazon Polarity Gemma 2 9B it scores

Amazon Polarity Gemma 2 9B it scores				
	Category	Precision	Recall	F1-Score
0	Negative	0.909774	0.975806	0.941634
1	Positive	0.975610	0.909091	0.941176
Overall	Overall	0.941406		

Table 6. YELP Review Polarity Gemma 2 9B it scores

YELP Review Polarity Gemma 2 9B it scores				
	Category	Precision	Recall	F1-Score
0	Negative	0.961977	0.988281	0.974952
1	Positive	0.987952	0.960938	0.974257
Overall	Overall	0.974609		

Again, an example of the G9 One Shot prompt used when testing the Gemma 2 9B it model can also be found below:

one_shot_en_2b = ""

Please perform Sentiment Classification task. Given the sentence, assign a sentiment label from ['negative', 'positive']. Return the label only without any other text.

Sentence: - Just bought my 1st iPad, iPad3, feeling real burned, mad, about iPad4 so soon. Grrr. REALLY mad!

Don't even care about mini now,"

Label: negative

Sentence: Kanye West was honored in a big way during Sunday night's MTV Video Music Awards by receiving

the Michael Jackso... Label: positive""

Both prompts, as well as the actual prompt engineering used during the research, were inspired by the work of Zhang et al. (2024).

Sentiment Classification

Both models, Flan T-5 XL and Gemma 2 9B, analysed the sentiment of each post using two-class (positive/negative) and three-class (positive/neutral/negative) classifications. In the two-class classification, sentiment was assigned a value of 1 for positive and -1 for negative. For the three-class classification, the values were 1 for positive, 0 for neutral, and -1 for negative.

Bigram Analysis

In addition to sentiment classification, word frequency analysis was conducted using the spaCy library. The analysis included both alphabetic and alphanumeric tokens, which are particularly important for AI model names (e.g., ChatGPT 3). Frequency tables of the most frequent bigrams (word pairs) were generated to highlight key terms and discussion patterns within each query group of the dataset. Each of the top bigrams was further analysed to calculate sentiment scores. The number of times each bigram was found in posts and the relevant sentiment score for that post was recorded, and added up to represent the frequency of the number of negative sentiment posts, posi-

tive sentiment posts, and neutral level posts that occurred in for each model and two and three class classification separately.

Exploratory Statistical Analysis

An exploratory analysis was conducted to understand the grouped posts within each search query. This involved examining the top flairs for each category to identify the nature of the content (e.g., discussion, news). For each of the query categories, a visual analysis of the timeline of the included posts in each query was done to visualise and track the discourse on each of the topics over time and track the popularity of each topic as well as the data as a whole.

Results of the research

The results of the data collection are described below and include the description of the retrieved posts, the flair analysis for each query subset, as well as a description of the sentiment analysis and bigram analysis.

Data

The dataset consists of 8,526 unique posts collected from 37 different queries. However, when examining the total number of posts retrieved by these queries, the cumulative count reaches 17,485. The top 5 queries with the highest number of posts include “AI” AND “Environment*” at the top with 2,724 posts. Following this, “AI” AND “energy” has 1,915 posts, and “GPT” AND “Environment*” ranks third with 1,265 posts. “ChatGPT” AND “Environment*” comes in next with 1,099 posts, while “OpenAI” AND “Environment*” also ranks high with 1,025 posts.

Additionally, queries such as “AI” AND “Sustain*” (934 posts), “AI” AND “Climat*” (930 posts), “GPT” AND “energy” (905 posts), “ChatGPT” AND “energy” (860 posts), and “ChatGPT” AND “Sustain*” (613 posts) represent other significant counts in the dataset. The bottom five queries of the top 10 queries clearly relate more to sustainability and AI than the first 5; this might be due to the language of the environment, which can mean the outdoor environment, such as nature, but also the programming environment. This will also be highlighted later in the bigram analysis.

In contrast, the bottom five queries represent more niche areas within the dataset. These include “OpenAI” AND “SDG,” returning just two posts, followed by “ChatGPT” AND “SDG,” which has three posts. “GPT” AND “SDG” have a slightly higher count with five posts, while both “AI” AND “SDG” and “OpenAI” AND “ESG” appear only six times each.

Flairs

The dataset consisted of 8,526 unique posts and contained a total of 7,169 flairs across all queries, as this is not a mandatory field when posting on Reddit. The top ten flairs for all the posts, including the count of their occurrence is shown in graph 1 below.

Overall, the dataset shows that “Discussion” is the most frequent flair, suggesting that these topics spark conversations and discussion. “AI” and “News” are also popular, indicating a focus on the latest developments in AI technologies. Queries related to “AI AND Environment*” and “AI AND energy” have the highest flair counts, highlighting strong interest in these particular areas. In contrast, queries like “AI AND SDG” and “OpenAI AND SDG” have again much lower total counts, which is also reflected in the number of retrieved posts.

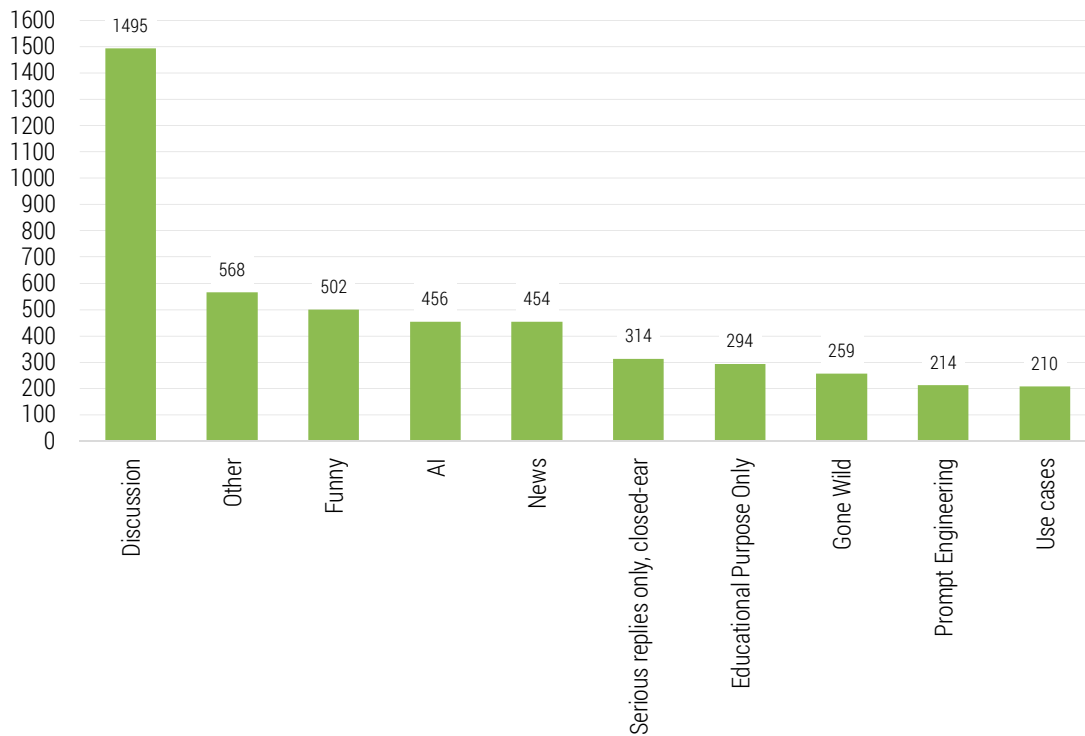


Figure 1. Top 10 Flairs Overall Data Table

Sentiment and Bigram analysis

To illustrate the finding, the top 5 queries and their top 15 bigrams can be found in the graphs below.

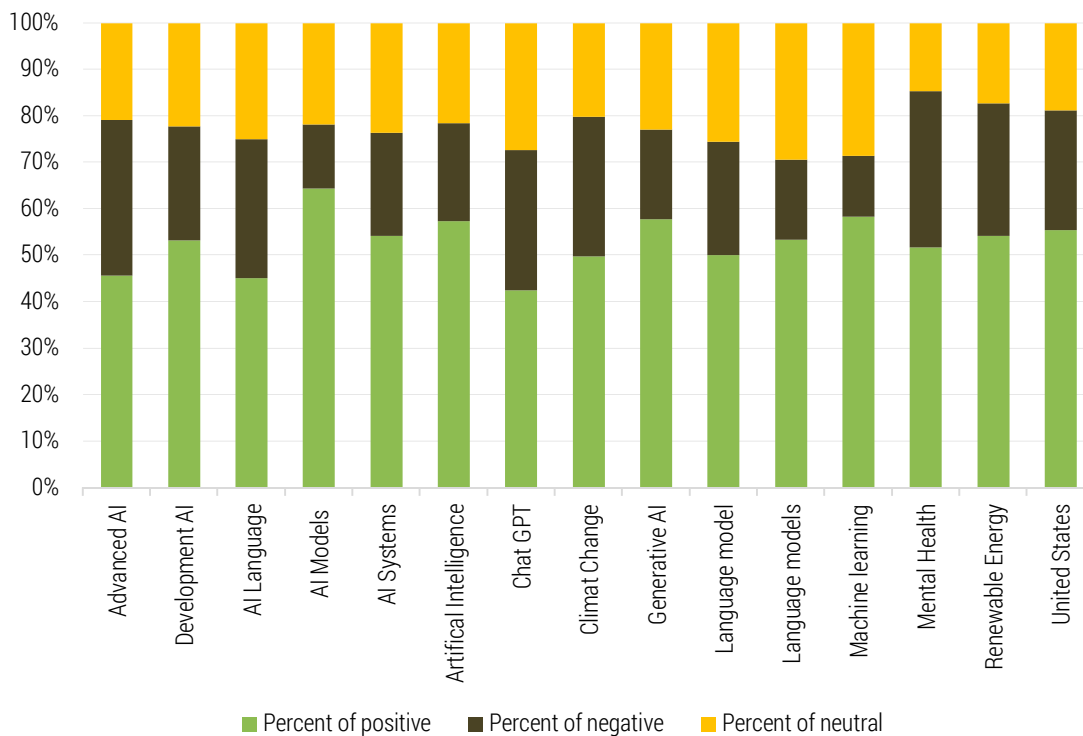


Figure 2. AI and Climat* Query

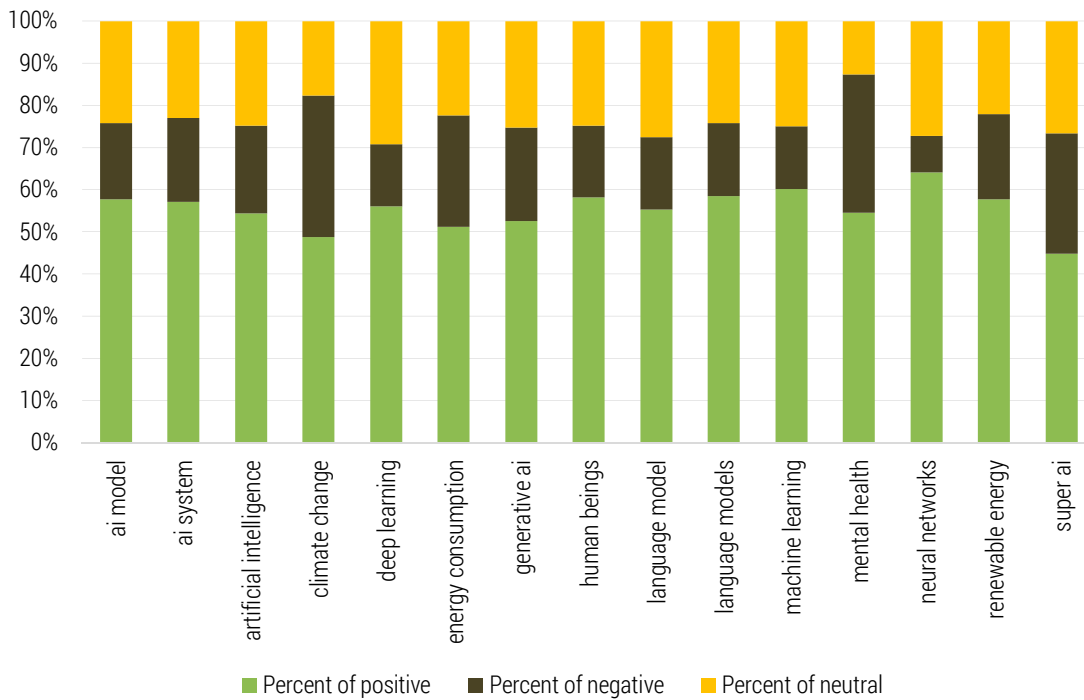
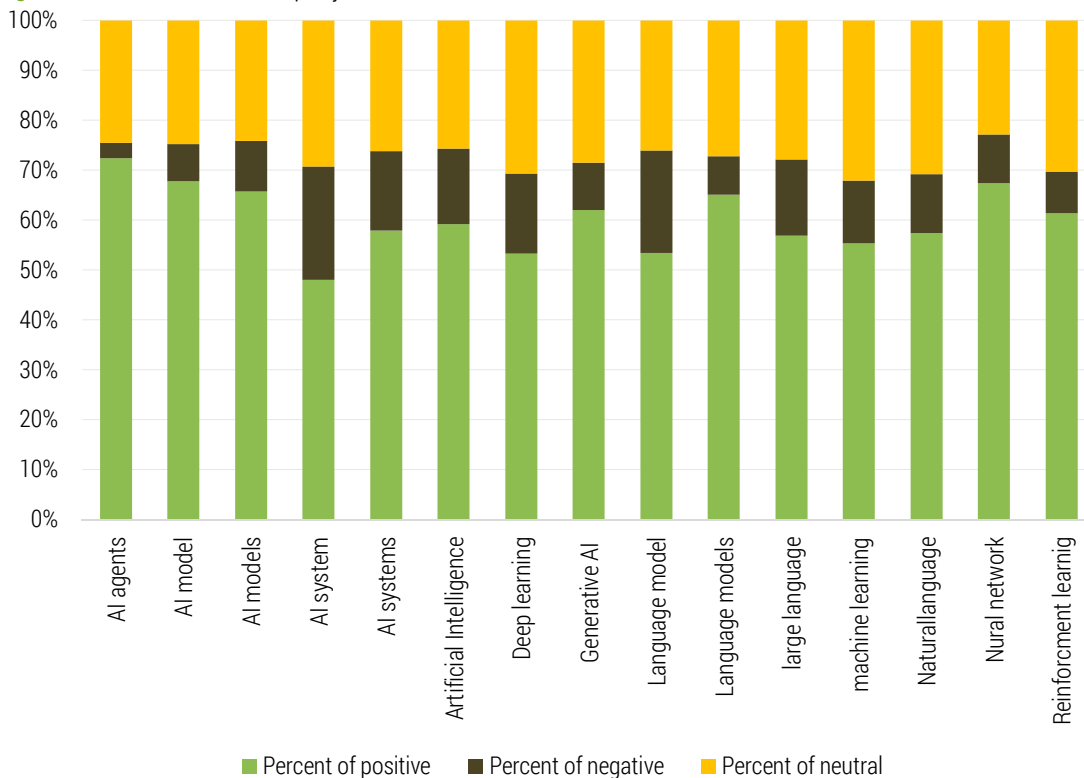


Figure 3. AI and Energy query

Figure 4. AI and Environment query



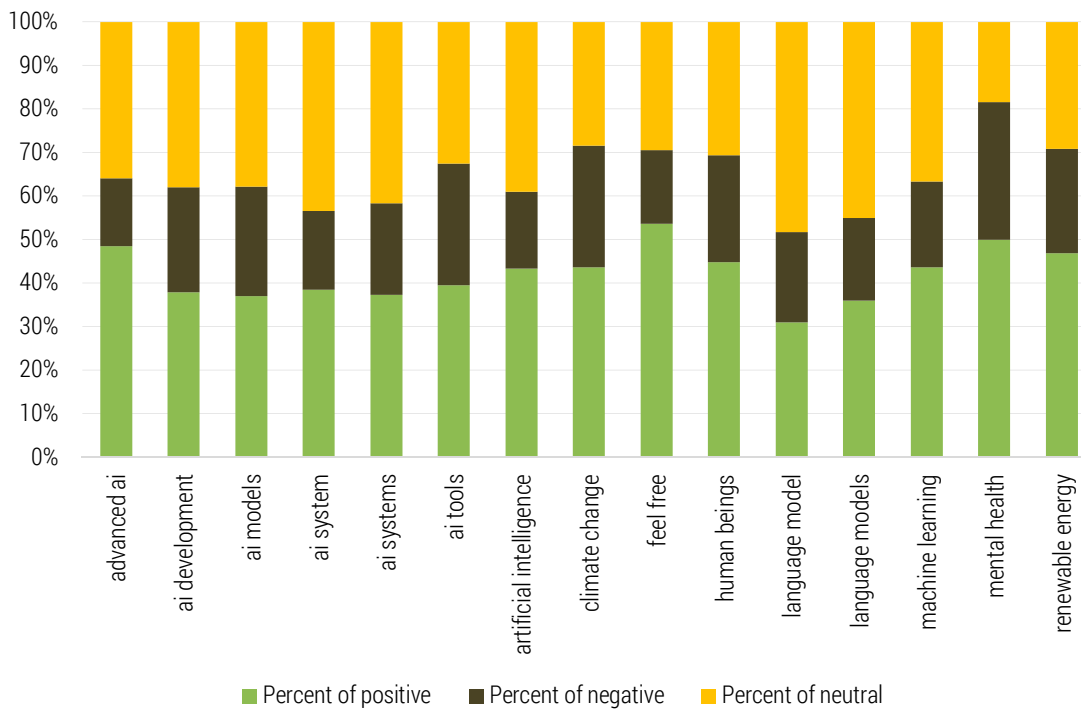


Figure 5. AI and Sustain* query

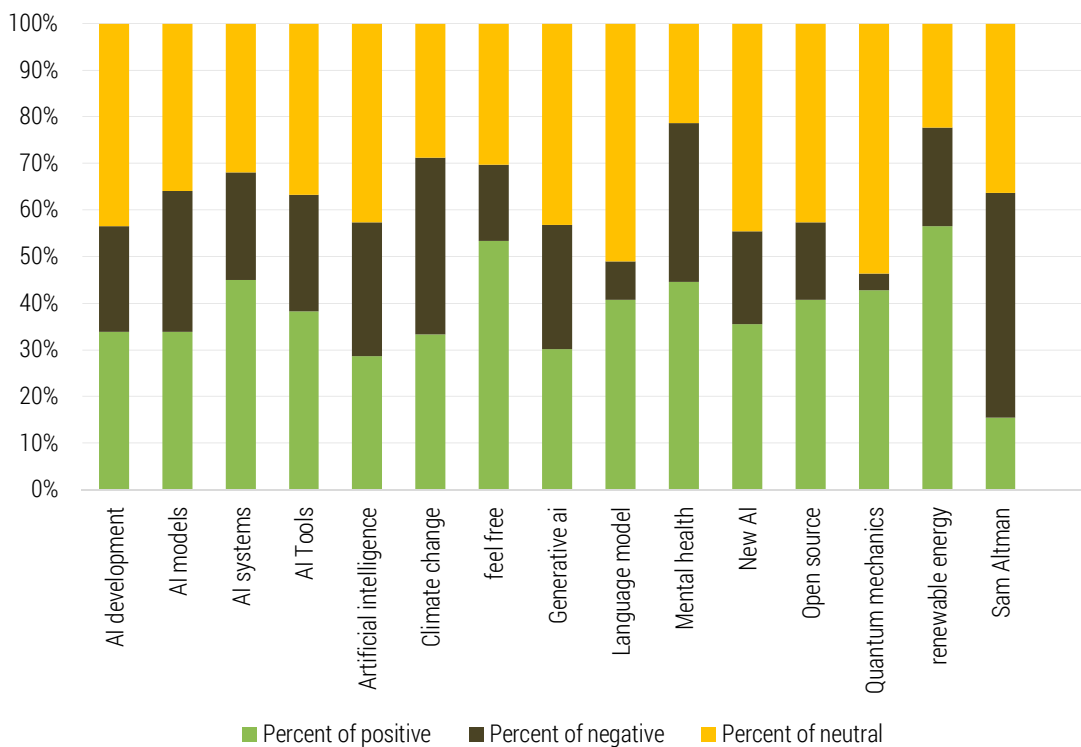


Figure 6. ChatGPT and Environment query

Overall sentiment analysis

From the pie charts below, we can see the overall sentiment analysis for each query and its top 15 respective bigrams. While both models generally detect more neutral and positive sentiment than negative, their relative proportions differ. Flan T5 XL leans toward classifying borderline or mixed expressions as neutral, whereas Gemma 2 9B it more readily interprets similar content as positive. These differences likely arise from variations in model architecture, training data, and the way each model interprets context. Nonetheless, both models converge on an overall picture of predominantly positive and neutral attitudes toward AI in sustainability, with negative sentiment forming a smaller but still noteworthy portion of the discussion.

OVERALL PERCENTAGE OF SENTIMENT FOR TOP 10 BIGRAMS
FOR EACH QUERY - FLAN T5 XL

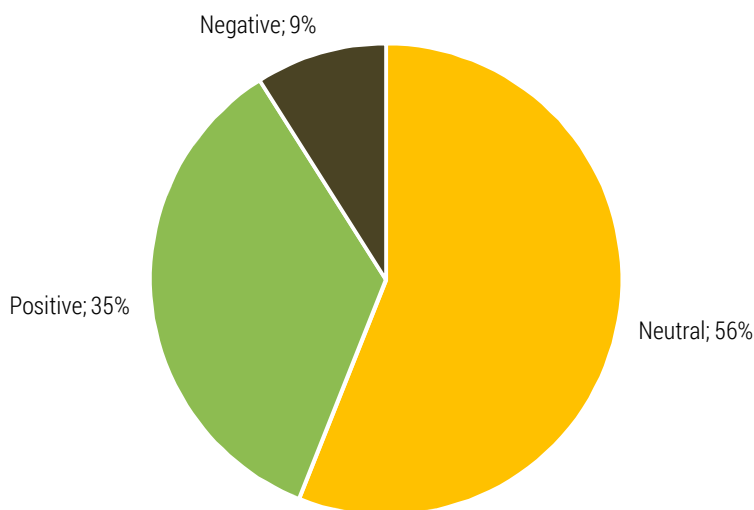


Figure 7. Sentiment percentage Flan T5 XL

OVERALL PERCENTAGE OF SENTIMENT FOR TOP 10 BIGRAMS
FOR EACH QUERY - GEMMA 2 9B IT

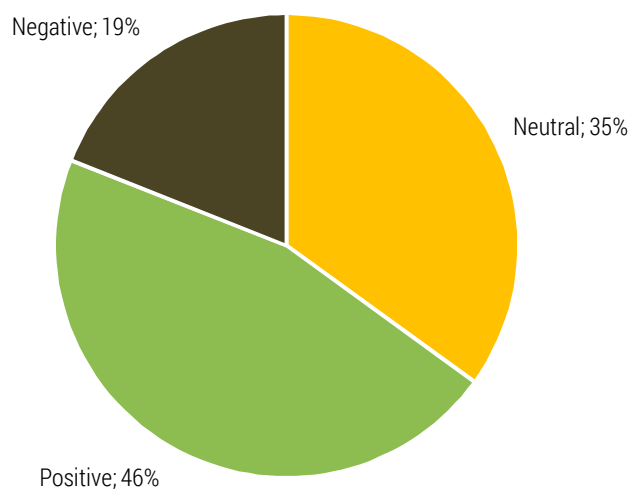


Figure 8. Sentiment percentage Gemma 2 9B it

Timeline plot of the retrieved posts

The timeline plot shows the time distribution of all the retrieved posts annually from 2011, with the first recorded retrieved post to 2024, totalling a timeline of the cumulative 17,485 posts.

Overall, the data reveals steady growth in AI-related discourse over the years, with a notable peak in 2023 and possibly even higher in 2024. This timeline plot graph, Graph 1 Timeline of all retrieved posts below, underscores the increasing prominence of AI in the context of sustainability. Similar graphs were also plotted for all the other queries, showing very similar results, but due to the limits of some queries, such as containing only one post, as well as overall research relevance, they were not included in this paper.

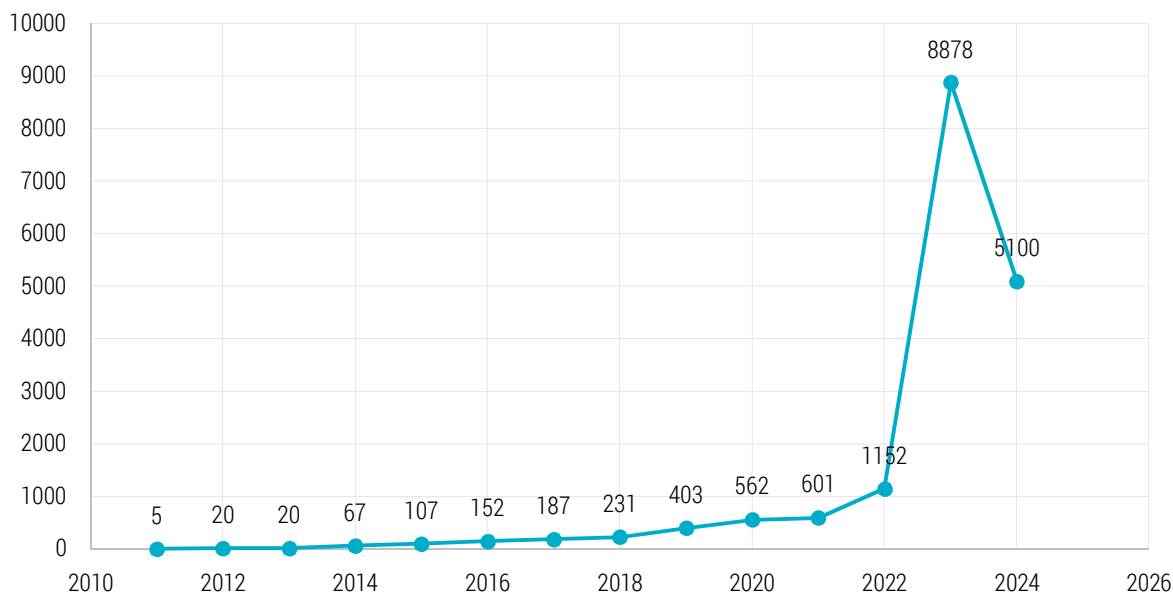


Figure 9. Timeline of all retrieved posts

Discussion

AI has rapidly evolved to become a transformative force across various sectors, significantly impacting sustainability efforts worldwide (Heaven, 2023; Jorzik et al., 2024). Beyond text-based language models like ChatGPT, AI applications optimise processes, enhance decision-making, and contribute to achieving the United Nations' Sustainable Development Goals (SDGs) (Haleem et al., 2022; Vinuesa et al., 2020; Schoormann et al., 2023).

Overall, the sentiment analysis revealed a predominantly positive public perception of AI's role in sustainability. Across various queries and terms, positive sentiments outweighed negative ones, suggesting that the public generally views AI as a beneficial tool in addressing environmental challenges. For instance, the query "AI" AND "Environment"* had the highest frequency with 5,187 mentions, and the sentiment analysis showed strong positive sentiments according to both LLM models. Bigrams like "Artificial Intelligence," "Climate Change," and "Renewable Energy" appeared frequently with high positive sentiments, indicating public recognition of AI's potential in areas such as climate modeling, energy efficiency, and environmental monitoring—topics extensively discussed in the literature (Das, 2021; Vinuesa et al., 2020).

However, the presence of negative and neutral sentiments indicates that public concerns and ethical considerations persist. Negative sentiments were notably higher for terms like "Reinforcement Learning" and "Neural Networks," possibly due to concerns about the energy consumption of training large AI models or ethical implications (Stahl, 2021). The significant neutral sentiments identified by the Gemma 2 9B it model suggest ambivalence or recognition of the complexity of AI's

role in sustainability, reflecting the literature's caution about AI's environmental footprint and the importance of considering the ethics of AI deployment (Naseem et al., 2021).

In general, however, the top bigrams for all queries were related to the technology of AI itself, such as "Machine Learning," "AI model," "Deep Learning," and so forth, showing perhaps the still-developing nature of AI implications. These bigrams frequently also had a higher positive frequency of sentiment categorisation than negative by both models, again showing general positive attitude and enthusiasm surrounding their existence and development.

The analysis of Reddit flairs complements these findings by providing context on how users categorise and engage with AI and environmental topics. The dataset consisted of 8,526 unique posts and contained a total of 7,169 flairs, as flairs are optional when posting on Reddit. The most frequent flair across the dataset was "Discussion," with 1,495 occurrences, indicating high engagement and supporting the sentiment analysis findings of active community involvement and nuanced discourse. The prevalence of phrases like "AI" (456 occurrences) and "News" (454 occurrences) reflects a keen interest in staying informed about the latest developments, aligning with the positive sentiments toward AI in environmental contexts.

Among the queries, "*AI AND Environment*"* stands out with the highest total flair count of 1,164, featuring flairs like "Discussion," "Research," "AI," "News," and "Project." This indicates strong interest and engagement in substantial discussions and information exchange on this topic. In contrast, queries like "AI AND SDG" and "OpenAI AND SDG" have much lower total counts, reflecting lower engagement and highlighting a potential gap between public discourse and the emphasis placed on these areas in the literature.

Further, the timeline plot data reflects a steady rise in AI-related discussions over the years, with notable peaks in 2022 and 2023. This surge can be closely tied to the rise of ChatGPT and OpenAI, which were explicitly used in many of the queries within this dataset. The release of ChatGPT brought AI into the mainstream, sparking widespread public interest and conversation. As ChatGPT demonstrated advanced AI capabilities, discussions around AI's potential, risks, and ethical implications significantly increased, explaining the dramatic spike in posts in 2023. However, as previously mentioned, the data for 2024 as previously mentioned is only until August 2024, and with the trend of increasing weekly ChatGPT users (Fried, 2024), it is not unreasonable to think this number of posts would have surpassed the year 2023 if it were collected near the end of the year.

Additionally, the growing awareness of climate change during this period contributed to an increased focus on how AI technologies can be leveraged for climate action. Queries related to AI and the environment, such as "*AI AND Environment*"* and "*AI AND energy*," were among the most frequently discussed topics, aligning with global conversations about sustainability and the role of AI in addressing climate challenges. However, it must be noted that the linguistic duality of the word environment, referring to nature as well as the programming environment, must be once again noted in this case. But when comparing the top 10 bigrams for the bottom five queries of the top 10 queries, we found similar results in the top bigrams.

The alignment of sentiment analysis results with the literature underscores the public's recognition of AI's potential benefits in sustainability, particularly in areas like climate change mitigation and energy efficiency. The positive sentiments reflect the literature's portrayal of AI as a tool for enhancing climate modelling, optimising renewable energy integration, and improving environmental monitoring (Chen et al., 2023; Hamdan et al., 2024). Conversely, the negative sentiments highlight concerns about AI's environmental footprint and ethical considerations, emphasising the need for responsible AI implementation (Stahl, 2021).

The consistent appearance of "mental health" across multiple queries is particularly noteworthy. It underscores the recognition of the intersection between environmental issues, AI, and human well-being, which were previously not identified in the literature review. Positive sentiments associated with this bigram reflect potential optimism about AI to support mental health services, perhaps in addressing climate-related stress and anxiety, which is becoming prominent, especially among young people (Soutar & Wand, 2022). Negative sentiments point to concerns about the ethical implications of using AI, perhaps in mental health contexts, such as privacy issues and the effectiveness of AI-driven interventions compared to human professionals.

Last but not least, this research paper has shown an innovative technique of applying closed LLM models to sentiment analysis with proven high-accuracy results. The use of these models is not only

an environmentally friendly solution as they omit the need to train new models and, therefore, produce more CO₂, but also showcases the option to build at-home de facto desktop solutions for researchers.

However, it is important to translate these findings into real world implementation and go beyond the realm of academic scope only. Translating these insights into actionable recommendations begins with a clear recognition that the data supports the development of targeted, evidence-based strategies. “renewable energy” supports the case for increased investment in AI solutions that drive sustainable development. At the same time, the significant negative sentiment observed for terms related to carbon emissions and high-energy-consuming AI models underscores the need for energy-efficient, green AI practices. Policymakers should invest in research programs and incentives to develop low-energy AI algorithms and systems, ensuring that technological progress does not exacerbate environmental issues. In addition, establishing transparent regulatory frameworks that mandate regular audits and reporting for AI systems in sustainability applications can help mitigate potential environmental impacts while ensuring ethical standards are met. Integrating real-time public sentiment data into the policy-making process will also enable adaptive governance that is responsive to evolving public concerns and environmental challenges.

For the business community, the rich data on sentiment and bigram frequencies provide clear signals regarding consumer priorities. The strong positive associations with terms like “renewable energy” and “climate change” suggest that companies have a significant opportunity to align their sustainability strategies with public expectations. By incorporating AI-driven sentiment analysis into their strategic planning and operational decision-making processes, businesses can refine product offerings, optimise resource allocation, and enhance energy management practices. Addressing consumer apprehensions—especially those related to the negative sentiment tied to technical terms—requires companies to invest in research aimed at reducing the energy consumption of their AI systems. Moreover, transparency in the use of AI for sustainability initiatives, coupled with clear communication of improvements in energy efficiency and ethical practices, can build trust and further reinforce a commitment to corporate sustainability.

The mixed sentiment surrounding technical AI terms also calls for coordinated, multi-stakeholder action. Addressing concerns related to the environmental and ethical impacts of AI demands interdisciplinary collaboration. Establishing advisory boards that include AI experts, environmental scientists, ethicists, policymakers, and community representatives will help develop robust ethical guidelines and standards for AI deployment. Such collaborative efforts can foster the creation of AI-driven monitoring systems to detect and counteract sustainability-related misinformation, ensuring that accurate, data-driven insights guide policy and practice. Additionally, public-private partnerships that bring together government agencies, private enterprises, and academic institutions are essential for accelerating the development and widespread adoption of sustainable AI solutions. These partnerships can pool resources and expertise, driving innovation while ensuring that advancements in AI align with the broader public interest and environmental goals.

In summary, these findings suggest that while there is significant optimism about AI’s potential to contribute to sustainability efforts, concerns need to be addressed, particularly regarding ethical implications and environmental impacts. For AI to fulfil its potential as a catalyst for sustainable development, it is crucial to promote responsible AI practices by developing and implementing technologies that are energy-efficient and ethically sound, minimising negative environmental impacts. Enhancing public awareness and engagement by increasing efforts to educate the public about AI’s role in achieving the SDGs can bridge the gap identified in public discourse. Incorporating public sentiment into policy and practice is essential to ensure that AI solutions align with societal values and needs.

Limitations

While our study provides valuable insights based on public sentiment on sustainability topics using AI-driven sentiment analysis, there are several limitations to consider. First, we treated Reddit posts as static texts, focusing solely on the posts without looking at, for example, the comments related to each post. Comments also express opinions as well as further interact with the ideas intro-

duced in posts. Future research could, therefore, expand by considering comments for each post, as well as considering the number of upvotes and downvotes for each post and comment to better understand the context and depth of it. This approach would also help to capture the discussion sentiments in a more dynamic way when further combined with time analysis.

Second, while we employed stand-alone language models like Flan T5 XL and Gemma 2 9B it for sentiment analysis, these tools could also be utilised to analyse other data sets and data types more accurately. In combination with their easy, prompt-based tuning, the data analysis process can be fast-tracked. For example, it can be easy to filter out spam or troll-like posts that introduce noise into the dataset, or asking the model to classify hate speech with one prompt. Overall, this could streamline and help achieve better accuracy in every aspect of working with the model and the data it is given.

Third, our study is limited to Reddit, which may not fully represent global public opinion, despite having an active user base of about 260 million weekly users. Expanding the research to include other similar platforms where discussions on AI and sustainability also occur, such as Twitter, with approximately 250 million daily users, and Discord, with an estimated 150 million daily users, could provide a broader and more diverse dataset. This would enhance the generalizability of our findings and offer a more comprehensive understanding of public sentiment across different social media landscapes.

By acknowledging these limitations and suggesting possibilities for future research, we aim to contribute to a deeper understanding of the dynamic relationship between AI and sustainability discourse. Leveraging AI's potential for rapid adaptation and analysis, future studies can inform more effective strategies for addressing all types of global challenges, not only environmental.

Conclusion

The integration of artificial intelligence into sustainability efforts presents significant opportunities and challenges, as evidenced by this study's findings. The sentiment analysis of Reddit posts revealed a predominantly positive public perception of AI's role in sustainability, aligning with the literature that emphasises AI's potential to enhance efficiency, enable data-driven decisions, and contribute to achieving several of the United Nations' Sustainable Development Goals.

Based on the research findings and supported by the literature, the following recommendations are proposed:

- Promoting the development and adoption of energy-efficient AI technologies: To address public concerns about AI's environmental footprint, policymakers and AI developers must prioritise energy efficiency in AI technologies. By reducing AI technologies' energy demands, stakeholders can mitigate negative environmental impacts and align AI development with sustainability goals (Chen et al., 2023; Hamdan et al., 2024).
- Integrating ethical considerations and the public in AI development: The intersection of AI, mental health, and environmental issues highlights the need for ethical frameworks and increased transparency. Clear communication about AI technologies, their benefits, and potential risks can build public trust and address uncertainties reflected in neutral and negative sentiments.
- Engaging with the public: Involving stakeholders in the dialogue about AI's role in sustainability ensures that development aligns with societal values and addresses public concerns. This was highlighted not only in the literature review but by this study as a whole, which produced unique findings in this discourse.

By implementing these recommendations, policymakers and organisations can address public apprehensions, foster trust, and promote the responsible integration of AI into sustainability initiatives.

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