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RESEARCH ARTICLE

Perceptions of the Future of Artificial Intelligence on Social Media: A Topic Modeling and Sentiment Analysis Approach

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ABSTRACT Today's AI technology has various applications in many fields, thus creating opportunities to improve different aspects of daily life and optimize business operations. However, there are also societal expectations and concerns regarding AI and its future impacts. Investigating such societal opinions and feelings is essential for social acceptance, further development and distribution of such technology, regulation, and adaptation to changes and policies. Despite this situation, such an exploration has not been sufficiently conducted in the existing literature and the most appropriate methods for such an exploration have not been sufficiently investigated. To contribute to addressing this limitation in literature, this study applies topic modeling and sentiment analysis approaches to investigate societal opinions and feelings about the future of AI on social media, which includes conversations from various segments of society. A corpus consisting of 16,611 comments and 998 unique Reddit post titles was analyzed with a customized BERTopic model for topic modeling and a BERT sentiment classification model. This study highlights the significant advantages of using BERTopic and BERT models in analyzing a large sample of social media discussions. The results of this study can help realize the potential of text analytics methods through transformer-based language models to derive empirical findings from large-scale data samples.

INDEX TERMS Artificial intelligence, BERT, BERTopic, sentiment analysis, topic modeling.

I. INTRODUCTION

Artificial intelligence (AI), established during the 1950s is continuously growing owing to rapid developments in deep neural networks, Big Data, and the massive growth of computational power [1]. These developments have provided AI systems the capacity to examine large datasets, identify complicated patterns, and make predictions with incredible precision and speed. Today, AI's image recognition capabilities emulate human visual and spatial perception skills; Bidirectional Encoder Representations from Transformers (BERT) models understand semantic patterns in text; machine translation algorithms mimic our language translation skills; chatbots like ChatGPT imitate aspects of human communication; AI makes decisions, even with reasoning capabilities through explainable AI [2], [3]. These incredible developments have led applications across diverse domains, from drug discovery to journalism [4], [5], [6], and entertainment including the game sector, where it can defeat human professional players in games such as chess and Go [7], thereby reshaping the world around us [8], thus a popular topic for a while.

Despite the ongoing interest, there are also varied opinions, feelings, misconceptions, concerns, expectations, and positive and negative attitudes [10], [11], [12] that need to be carefully considered, including those about the risks related to ethics [12] and other societal positive or negative effects of AI. Understanding these perceptions and attitudes toward AI is crucial for social acceptance, adoption [13], shaping the further development and deployment of that technology [14], research funding, commercial development, regulation [15], and adapting to changes and policies. Therefore, as AI continues to evolve, exploring society's perceptions and attitudes toward *AI and its future* is critical, thus identifying as much relevant information obtained from diverse members of society as possible is essential to facilitate the future steps to be taken [16] for AI development.

However, few studies explored perceptions and attitudes about the future of AI, and they have generally employed surveys or interviews [8], [17]. Information received from

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surveys and interviews was commonly limited to the questions determined in the research design, respondents' understanding of these questions, and the time when these surveys or interviews were conducted [18]. Contrary to this limitation, social media platforms can naturally reflect a wide range of contemporary and spontaneous perceptions and attitudes of a diverse society. Social media data are created spontaneously, where individuals with diverse backgrounds, personal experiences, and viewpoints share their most recent ideas honestly since social media is an easily accessible and comfortable tool [19]. However, how *AI and its possible future impacts* are discussed on social media, which reflects the public's opinions and feelings [10], [12], [20], remain unexplored. Thus, in this article, we analyze social media data to search society's opinions, attitudes, perceptions, and expectations about the future of AI.

Several studies utilized manual content analysis to mine social discourse within text data extracted from social media [23] [24], but they could analyze a limited amount of data. This is because manual analysis and summarizing of society's attitudes and perceptions are very challenging because of the volume of conversations produced on social media. To address this challenge, the application of Natural Language Processing (NLP) techniques is crucial if we need to analyze large volumes of text data [10], [16], [20], [23], [24], [25], [26], [27]. This research, therefore, applies topic modeling and sentiment analysis methods.

This study reviewed current topic modeling methods and found BERTopic to be the most appropriate approach for topic modeling in our case. Hence, we investigate the application and usefulness of BERTopic, a cutting-edge transformer-based language model [28]. To gain insightful information about the topics society discusses about the future of AI, we apply this novel topic modeling technique to a large sample of social media discussions, to 998 unique Reddit post titles and 16,611 comments. We also briefly reviewed current sentiment analysis methods, found a BERT model to be the most suitable method for sentiment analysis in our case, and finetuned a pre-trained BERT model for sentiment classification. We customized the hyperparameters for both models (i.e., BERTopic and BERT), chose the optimal models based on the evaluation metrics, and used these models to obtain empirical findings within the corpus we built.

The key contributions of this article are provided below:

Identifying Common Topics and Sentiments: This work identified common topics and attitudes expressed in social media discussions about AI, thus providing diverse perspectives of society about relevant public views and sentiments. These insights can enlighten further (AI development and usage) - related decisions of policymakers and researchers.

Combining Topic Modeling and Sentiment Analysis: This work combined topic modeling and sentiment analysis by building BERTopic and BERT models, applied these models to a real-world scenario and achieved more efficient results than previous traditional methods.

The structure of this study is as follows: The relevant literature is discussed in the second section. We then go over our sampled data and the methods we used. Key study findings are presented in the fourth part. The work is concluded in the fifth section, which discusses important findings and research implications.

II. LITERATURE REVIEW

This literature review includes two main bodies of the literature including topic and attitude identification methods.

A. TOPIC IDENTIFICATION

A limited amount of research has examined topics society discusses the future of AI that reflect societal opinions and perceptions; and most of them have used surveys and interviews [8], [17]. Survey and interview data were typically restricted to the questions outlined in the research design, the comprehension of the questions by the respondents, and the duration of the survey or interview [66]. Recent research studies tended to find new data sources like text data to understand general opinions and feelings about AI, such as newspapers [11], [29], [30], [31]; and implemented different techniques to identify topics in the text.

Content analysis was the first prominent technique, as seen in [13] and [29]. A deductive strategy technique was used by [13], namely a deductive content analysis based on the topics described in prior research to examine AI-related topics in five major American newspapers between 2009 and 2018. According to that study, people were more likely to emphasize the advantages of AI than the drawbacks, but they were more detailed when discussing the hazards. In [29], a deductive content analysis to find AI-related topics discussed in the newspapers during the COVID-19 pandemic was conducted.

Some studies combined different methods. For example, in [30], both content analysis and text classification algorithms were utilized. A dataset comprising over 3 million New York Times articles spanning 30 years was analyzed to observe topics and attitudes that are connected to discussions about AI. More specifically, first, 8000 AI-related paragraphs were annotated by Amazon Mechanical Turk (AMT) workers, and annotations for attitudes about the future of AI (from pessimistic to optimistic) on a 5-point Likert scale were gathered. Second, specific hopes (e.g., positive impact on work) and concerns (e.g., loss of job) were determined based on finer-level annotations. Third, binary labels for whether hope or concern exists in the paragraph were found by AMT workers. These annotations form their ground truth to classify new paragraphs based on paragraphs' hope or concern inclusion. That research revealed that discussions about AI have generally leaned more toward the positive side since 2009 [30]. However, recent investigations observed in that research indicated growing concerns about AI losing control, ethical dilemmas, and adverse effects on employment [30]. Additionally, the data illustrated increasing expectations for AI in healthcare and education over time. In [11], a mixed

methodology was applied by combining automatic content analysis for clustering through topic modeling and manual coding to analyze 1776 news articles harvested from four newspapers (i.e., the New York Times, Washington Post, the Guardian, and USA Today) for exploring how AI has been portrayed in the past decades.

We also used topic modeling in this study and before choosing the most appropriate topic modeling approach in our case, we reviewed different topic modeling techniques.

1) TOPIC MODELING

Currently, topic modeling has become a frequently used NLP method among computational scholars [32]. Topic modeling ''is a text mining technique which automatically discovers the hidden themes from given documents'' [33, p. 1].

Diverse topic modeling techniques and their comparisons based on data analysis are handled in prior work. For instance, three different topic model algorithms, Latent Semantic Analysis (LSA), Non-negative Matrix Factorization (NMF), and Latent Dirichlet Allocation (LDA) were employed in [33] to explore the topics of a large number of tweets and found that LDA results outperformed the former two algorithms.

The *LDA topic modeling* approach has been the most wide-ranging traditional topic modeling method so far [34]. This method is an unsupervised text analysis approach utilized for finding groups of words that characterize the given documents. This approach was introduced by [35], depicting it as a probabilistic model for collecting discrete data like text corpora. In LDA topic modeling, each document in the corpora is modeled as a combination of a collection of topics' probabilities, and each topic is modeled as a mixture of a set of word occurrence probabilities. This method expands classical natural language processing methods such as the unigram model and Latent Semantic Analysis [36]. This technique is different from the term frequency models since it is mixed-membership modeling [36]. In the unigram model, each word is illustrated from the same term distribution, and each word in a document is illustrated from the term distribution of the topic [36]. In mixed-membership models, however, documents are expected to belong to several topics, and the topic distributions differ based on documents [36].

Several limitations of the LDA topic modeling method have drawn attention. First, it neglects semantic relations among words [34] since the method focuses on word occurrence probabilities. Second, it requires manually determining hyperparameters such as the number of topics (k). These determinations complicate topic modeling processes and affect the quality of the model. Moreover, LDA does not allow uncorrelated topics because it is based on frequencies of the common occurrence of words-topics probabilities. Finally, it requires word-document matrices before running topic modeling, which takes additional time and human effort.

With the latest advancements in the NLP field, novel topic modeling techniques have emerged such as Corex, Top2Vec, and BERTopic [34]. BERTopic mainly addresses these limitations of LDA topic modeling and offers more advanced functions such as search functions (e.g., searching topics associated with a specific word, easily going from topic to documents), and hierarchical and dynamic topic modeling. Furthermore, as different from the LDA, BERTopic does not require intense preprocessing (removing stop-words, stemming, and lemmatization of text) to produce a better topic model [28]. Moreover, including BERTopic, several topic modeling methods (e.g., LDA, NMF, and Top2Vec) were compared in prior research as in [27], [28], and [34] and indicated the potency of BERTopic in analyzing text data.

Despite BERTopic's many advantages, a few disadvantages also exist that come with it. First, its embedding approach may result in too many topics, demanding labor-intensive examination of each topic. Likewise, it may produce many outliers [67].

These mentioned disadvantages, however, are not barriers to the proposed study. There is a function to reduce the number of topics. Moreover, parameters can be customized to reduce the number of topics. To address the limitation concerning outliers, BERTopic specifies outliers by -1, thereby they can be easily excluded from the results. Thus, we use the BERTopic model due to its highlighted advantages.

B. ATTITUDE IDENTIFICATION

Attitudes are considered to be a link between humans and their environment and play a crucial role in comprehending human behavior [37]. Earlier research conducted to explore attitudes was mostly based on surveys and interviews. Researchers are now able to identify attitudes in text using a variety of computational methods. In this study, we use sentiment analysis to determine whether the text reflects a positive or a negative attitude. We review some of the sentiment analysis approaches in the next section.

1) SENTIMENT ANALYSIS APPROACHES

There are useful open-source sentiment analysis tools available for academics analyzing emotions and attitudes. For instance, with just a few lines of R code, the R syuzhet package can identify eight emotions (anger, fear, anticipation, trust, surprise, sorrow, joy, and disgust) from a significant amount of text data. Negation, however, is not covered by this package (for example, ''we don't need to fear AI'').

The R sentimentr package, which deals with negation, was made available to create text sentiment polarity, or positivity or negativity, although it does not expose distinct emotions like fear. Other well-known dictionary-based, user-friendly open-source sentiment analysis tools that examine polarity include Python programs like VADER and TextBlob.

Another extensive technique to examine attitudes and emotions in the text is linguistic inquiry and word count (LIWC) [21], [22]. The text analysis tool LIWC ''counts words in psychologically meaningful categories…[such as] attentional focus, emotionality, thinking styles, and individual differences'' [38, p. 24]. To accurately represent people's social

and psychological situations in text, LIWC additionally uses a dictionary-based method that includes more than 100 definitions. To determine the percentage of all the words in a given text that fall into each of the dictionary categories, LIWC scans the text and compares each word to a list of dictionary terms. However, contextual meaning is critical for the NLP problems. Thus, using word counts to identify emotions and attitudes in text requires more validation and analysis, even though employing dictionary-based methodologies is common [39].

In the latest studies, BERT-based models (e.g., BERT, RoBERTa, DistilBERT) have been suggested as state-of-the-art models for text classification [40], including sentiment analysis [16], [41], [42], [43], and revealed quite successful results compared to other models [40]. They can produce a more accurate representation of the text by taking into account both the left and right sides of a word to capture its contextual meaning [40], [44]. Although BERT-based models have many benefits and capacities, training them requires a lot of training data, computational power, and time [6], [40]. One of the solutions to that challenge is using pre-trained models and finetuning them for the desired NLP tasks [6]. In this study, we put this solution into practice, obtained a pre-trained model, and finetuned it to investigate attitudes by utilizing the ktrain library [45].

Even though this literature review demonstrated the superiority of BERTopic and BERT models over other similar methods, few studies have explored the potential of BERTopic and BERT models in real-life case studies [20], [27], [45], according to the related literature. Additionally, the majority of the published papers analyze Twitter data [24], [34]. Another important gap in the extant literature is the absence of strong experiments with appropriate evaluation metrics for model selections. To address those gaps, by selecting the optimal BERTopic and BERT models based on the appropriate evaluation metrics and implementing them on a large sample of Reddit conversations, this study is contributing to expanding the literature on BERTopic and BERT applications and public opinions and feelings regarding the future of AI.

The details of the implemented methods are explained in the methodology section.

III. METHODOLOGY

The workflow of the research methodology to be followed in this study is represented in Fig 1. The analysis in our study comprises two main components: topic modeling and sentiment classification. The details are described in the next sections.

A. RESEARCH SITE: REDDIT

In social media research, X (formerly Twitter) is commonly employed [46]. Users frequently remark on current events and tweets are regarded as ''public,'' making the website a useful source of observational data [46]. The website formerly featured open APIs that made gathering data simpler. Reddit has drawn academics' attention as a data source during the past ten years [47], [48] due to the similar advantages X offers. Moreover, Reddit enables users to anonymously discuss a given subject in subreddits dedicated to that subject. The massive community on Reddit is made up of hundreds of smaller sub-communities called ''subreddits,'' each of which focuses on a particular topic, with over 50 million daily active users. These advantages make Reddit an ideal venue for studying public opinions and attitudes [49].

To answer their research questions, researchers can select the proper subreddits as samples and have access to information offered by Reddit users on a range of subjects. Reddit data is open to everyone, and the usernames of posters are not their real names. Hence, using Reddit data for research purposes typically exempts from institutional ethical review [10], [46]. Reddit has been utilized as the data source in our study.

To illustrate interpretations on Reddit, we include exact quotations in the findings section. The quotes' exact meaning is crucial to our study; therefore, we did not paraphrase the quotations. To keep Redditors' identities private, we did not publish their usernames.

We chose the subreddits based on our research purpose as described in the next section.

1) SELECTION OF SUBREDDITS

Subreddits concerning the future of AI were selected for this work. To inspect which subreddits comprise the future of AI-related discussions, a keyword search of *artificial intelligence (AI)* was first conducted. Due to their inclusion of posts linked to the future of AI and their descriptions, we determined fifteen subreddits to be included in this study (shown in Table 1). More specifically, they (1) explicitly focused on future trends (Futurology, tomorrowsworld, DarkFuturology, conspiracy), (2) specifically focused on AI (ArtificialIntelligence, artificial, agi, MachineLearning, deeplearning, Automate, singularity), or (3) focused on news and discussions about technology and science around the world that also comprise various current AI-related conversations (e.g., worldnews, science, tech, technology).

B. DATA COLLECTION AND CLEANING

We utilized the Reddit API via PRAW (Python Reddit API Wrapper) to capture posts and comments from the selected subreddits. All posts within these subreddits containing the terms ''Artificial Intelligence,'' ''AI,'' ''artificial intelligence,'' or ''Artificial Intelligence'' were collected, along with their corresponding top-level comments. Following data extraction, we identified and removed comments marked as ''deleted'' or ''removed,'' as well as phrases of ''please reply to OP's comment here'' or ''the following submission statement was provided by…'' These entries were excluded without performing further data cleaning (e.g., removing stop words, etc.) to retain the originality of the meaning of the post titles and comments to be analyzed by BERT-based models. This process yielded a

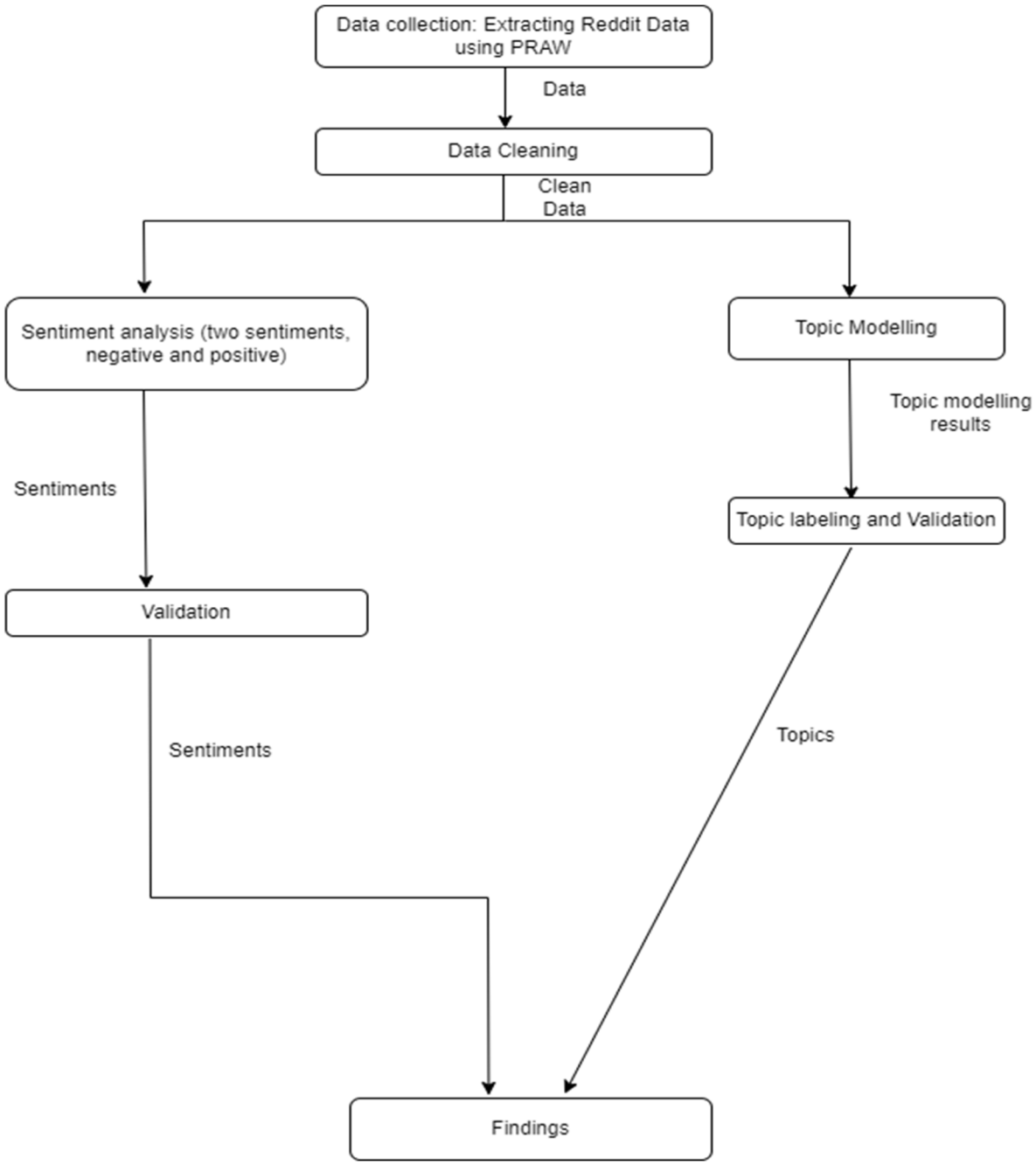


FIGURE 1. Data analysis steps.

total of 998 unique post titles and their corresponding top-level comments, a total of 16,611 comments, which were shared by 671 unique users from 2/19/2013 to 7/3/2022 were analyzed. The distribution of the posts and the comments by years and subreddits is depicted in Fig 2 and Fig 3, respectively.

C. IMPLEMENTATION

1) BERTOPIC

BERTopic models bolster clustering methods through a class-based variation of TF-IDF to produce coherent topic representations [28]. Three stages through which BERTopic produces topic representations, c 1) document embedding, 2) document clustering (i.e., by UMAP reducing the dimensionality of embeddings, and by HDBSCAN clustering reduced embeddings and creating clusters of semantically similar documents, 3) creating topic representation (extracting and reducing topics with c-TF-IDF) [28], [45], as illustrated in Fig 4.

In the first stage, BERTopic utilizes the Sentence-BERT (SBERT) framework, and each document is transformed into its embeddings to produce representations in vector space through sentence transformers [28], [45]. Sentence embed-

TABLE 1. Information about subreddits.

Subreddit	Description of Subreddit	Number of Members
Futurology	A subreddit devoted to the field of Future(s) Studies and speculation about the development of humanity, technology, and civilization.	15.6m
tomorrowsworld	A subreddit for the future of the world conversations	816
DarkFuturology	A subreddit for dystopian trends.	68.1k
conspiracy	The conspiracy subreddit is a thinking ground. Above all else, we respect everyone's opinions and ALL religious beliefs and creeds. We hope to challenge issues that have captured the public's imagination, from JFK and UFOs to 9/11. This is a forum for free-thinking, not hate speech.	1.7m
ArtificialInteligence	A subreddit for Artificial Intelligence conversations	78.1k
artificial	A subreddit for Artificial Intelligence conversations	153k
agi	A subreddit for Artificial general intelligence (AGI) conversations, which is also referred to as "strong AI", "full AI" or as the ability of a machine to perform "general intelligent action."	12.1k
MachineLearning	A subreddit for Machine Learning conversations	2.5m
deeplearning	A subreddit for Deep Learning conversations	80.2k
tech	A subreddit dedicated to the news and discussions about the creation and use of technology and its surrounding issues.	11.4m
technology	Subreddit dedicated to the news and discussions about the creation and use of technology and its surrounding issues.	12.2m
worldnews	A place for major news from around the world, excluding US-internal news.	29.1m
science	This community is a place to share and discuss new scientific research. Read about the latest advances in astronomy, biology, medicine, physics, social science, and more. Find and submit new publications and popular science coverage of current research.	27.7m
Automate	A place for the discussion of automation, additive manufacturing, robotics, AI, and all the other tools we've created to enable a global paradise free of menial labor. All can share in our achievements in a world where food is produced, water is purified, and housing is constructed by machines.	47.1k
singularity	Everything pertaining to the technological singularity and related topics, e.g., AI, human enhancement, etc.	150k

dings function by utilizing contextualized word embeddings for complete phrases as opposed to single words. BERTopic is taking advantage of the Sentence Transformers library, which includes a range of pre-trained sentence embedding models [28], [45]. Generally, the number of dimensions is 384 for mini models like the BERTopic default: MiniLM and 768 for bigger models [45].

The input embeddings' dimensionality reduction is a key component of BERTopic because high dimensional embeddings make clustering challenging [28]. Thus, the second stage is devoted to that problem. One way to solve this problem is to make the embeddings less dimensional so that clustering algorithms can operate in a manageable dimensional space (such as 5) [28].

Because Uniform Manifold Approximation and Projection (UMAP) can capture both the local and global high-dimensional space in lower dimensions, it is employed by default in BERTopic [28]. Nonetheless, alternative methods, such as Principal Component Analysis (PCA) are also presented for that step [28]. After reducing the dimensionality of the input embeddings, the Hierarchical Density-Based Spatial Clustering of Applications with Noise (HDBSCAN) algorithm is preferred to cluster those embeddings, since UMAP and HDBSCAN cooperate well, even though k-Means is also proposed as an alternative technique in [28].

In the last stage, from these clusters, topic representations are obtained utilizing a custom class-based variation of TF-IDF [28]. After concatenating all papers related to a topic into a class called class c, the frequency of each term (word) in the class is determined and divided by the total number of words. This enhances the topic model by highlighting a term's significance inside a cluster as opposed to a single document [28], [45].

Before changing hyperparameters and diving into these stages described above, we processed the cleaned Reddit text

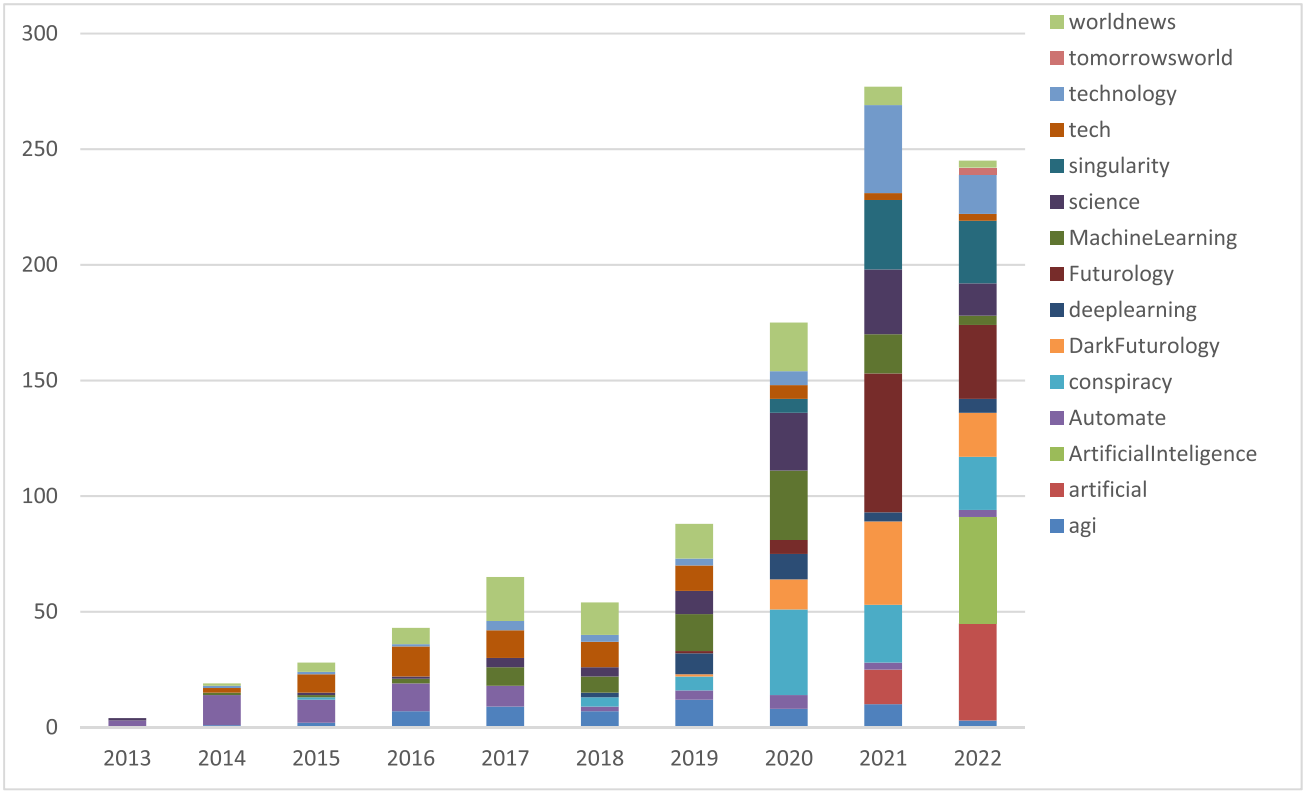


FIGURE 2. The number of posts by years and subreddits.

data in Python for topic modeling by the BERTopic model (not customized). This original model created 231 topics; 7187 submissions did not belong to any of these topics shown as -1 which refers to all outliers. To identify and interpret topics properly, we decreased the number of topics. To do so, first we used topic reducing function as "model.reduce_topics (documents, topics, nr_topics = "auto")" since that function merges topics together that are very similar, but it still gave us many topics, 195 topics, which complicates identifying and interpreting topics and making appropriate inferences. Because of this, we customized the hyperparameters of the algorithms constituting BERTopic and performed experiments to obtain a reasonable number of clusters to be interpreted properly.

Before beginning the experiments, we investigated the hyperparameters to be tuned and the most appropriate evaluation metrics to find optimal hyperparameters in our case. In previous topic modeling studies, *the number of topics* has been commonly used as the hyperparameter, and *topic coherence* and *topic diversity* have been widely used as evaluation metrics for hyperparameter optimization [27], [28], [45]. Different models with different numbers of topics were tested in those studies, and the model resulting in the highest topic coherence and diversity was chosen. In other words, the model that best combines similar topics and separates dissimilar topics was selected. *The number of topics* has been generally preferred since it is comparable when different topic modeling methods such as LDA, NMF, BERTopic are used in the experiments to choose the best method. However, our aim in this study is to find the best BERTopic model by finding the optimal hyperparameters and to apply this model to a real-life case, rather than experiencing which topic modeling approach is better, because previously published work has already shown the superiority of BERTopic over other different approaches. Thus, we focused on the hyperparameters of the algorithms constituting BERTopic, specifically UMAP (i.e., *n_neighbors, n_components, min_dist, and metric)* and HDBSCAN (i.e., *min_samples, min_cluster_size, metric, and cluster_selection_method)* listed in [28].

In terms of evaluation metrics, *topic coherence,* specifically Normalized Pointwise Mutual Information (NPMI) has been mainly utilized for semantic similarity by linking it to human judgment [27], [28]. This association, however, might not exist with neural topic models, according to recent research [28], and it might only be valid for classical models [28]. Moreover, human assessment of a topic is regarded as the gold standard when determining topic quality [27], [28]. Human assessment is a costly and resource-intensive method to put into practice, though. Hence, the focus of the extant literature has been on automatically measuring coherence parameters, deeming that they closely resemble human judgment.

Taking all this information into consideration, we first searched for the most appropriate automatic evaluation met-

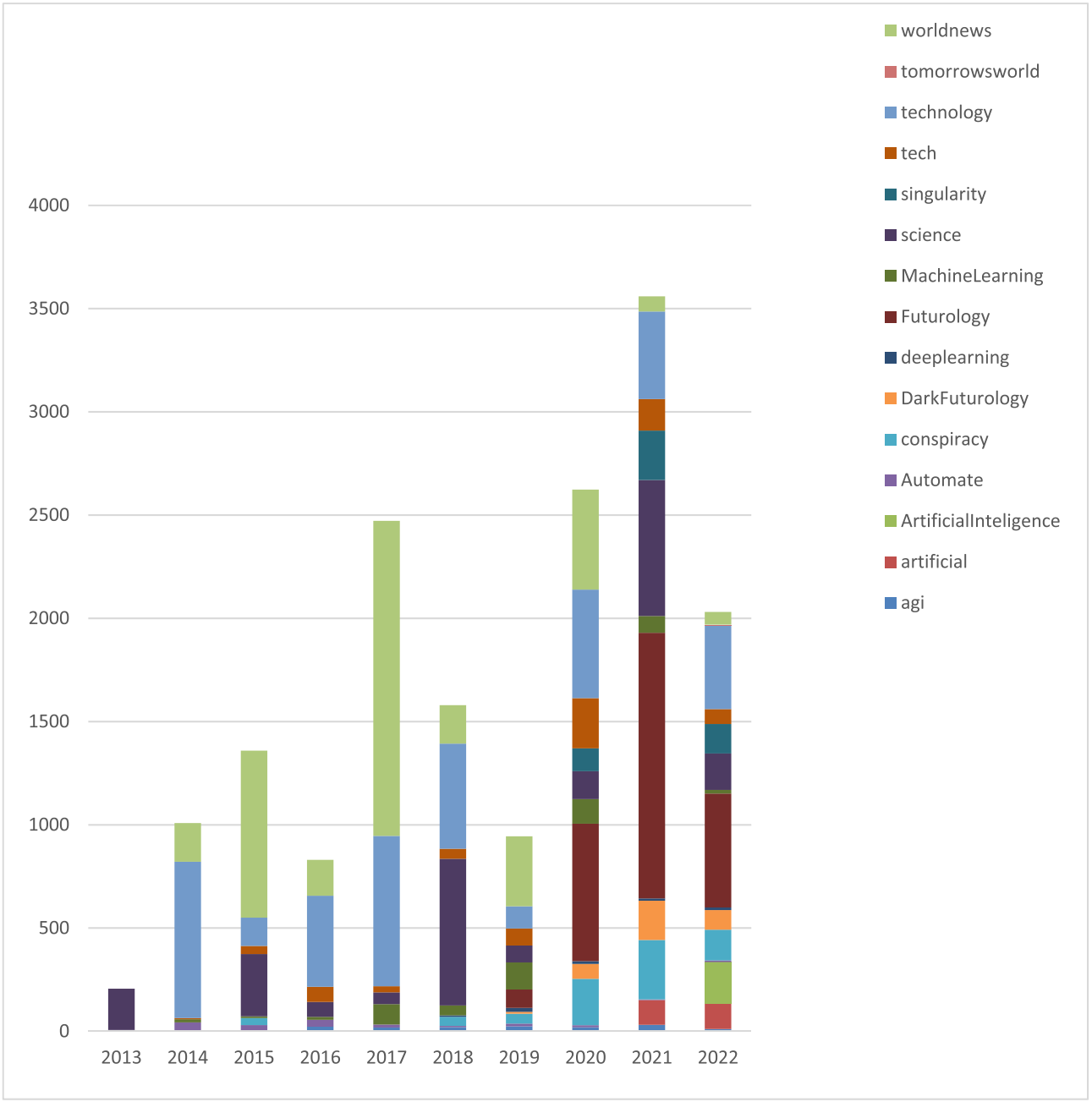


FIGURE 3. The number of comments by years and subreddits.

rics to find optimal hyperparameters in our case and then validated the findings with human judgment. Because we use a neural topic model [28] in this work, rather than using NPMI and *topic diversity* metrics, we searched for alternative evaluation metrics. We determined the evaluation metrics as appropriate to the hyperparameters of UMAP and HDSCBAN algorithms: *trustworthiness score* which shows how much data remains the same after dimension reduction by UMAP [50], [51] and *density-based clustering validation (DBCV) score* which shows how much the same clusters are dense, and the different clusters are not dense after clustering by HDBSCAN [52].

We began the experiments with a sentence embedding procedure, by using the "all-MiniLM-L6-v2" sentence-transformers model that maps sentences to a 384-dimensional dense vector space. We chose this default model for embedding in BERTopic documentation since it is a smaller and faster model [28]. Next, we searched for the optimal hyperparameters for UMAP (i.e., *n_neighbors, n_components, min_dist,* and *metric)* and HDBSCAN

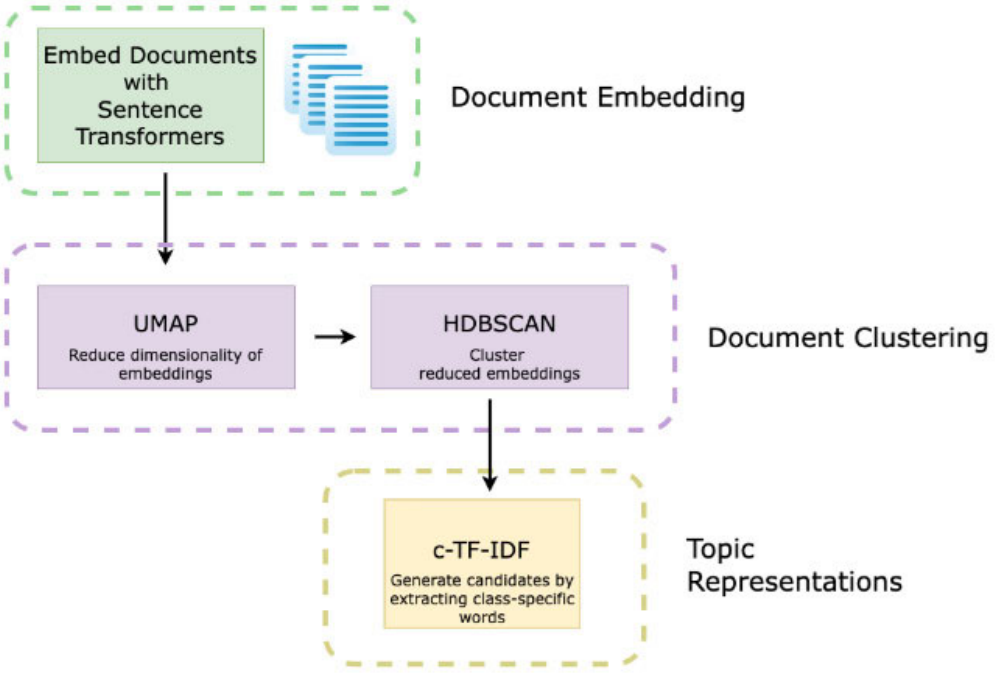


FIGURE 4. BERTopic algorithm components [28], [45].

(i.e., *min_samples, min_cluster_size, metric,* and *cluster_selection_method)* specified in [28].There are few studies conducting experiments to find optimal UMAP and HDBSCAN parameters while using BERTopic as in [45], and only the *minimum topic size* as an HDBSCAN parameter was considered in the experiments [45]. Rather than focusing solely on the *minimum topic size* or *the number of topics*, we tuned almost all the UMAP and HDBSCAN parameters specified above. Since there are many parameters, performing experiments by changing all the parameters at the same time was quite challenging. First, we set the parameters of a UMAP model as *n_neighbors* =200, *n_components* =3, *min_dist* =0.1, *metric* = ''euclidean'' following the instructions stated in UMAP and BERTopic documentations. We recorded the *trustworthiness* score of this first UMAP model. Then, we searched for the optimal parameters of HDBSCAN to be combined with the initial UMAP model, by ranging *min_samples* from 1 to 50, *min_cluster_size* from 35 to 300, and changing *cluster_selection_method* as ''eom'' or ''leaf'', and setting *metric* fixed as ''euclidean'' to find the parameters that gave the highest *DBCV score*. This process resulted in optimal HDBSCAN parameters and the best DBCV score to be achieved using the parameters in the given range for the first UMAP model, as shown in Fig 5.

We built two more UMAP models by changing the UMAP parameters. For the second and third UMAP models, we repeated the same procedure for finding optimal HDBCSAN parameters for each model and noted the DBCV scores. In the end, we chose the model with the highest *trustworthiness* score (the second UMAP model with a 0.94 *trustworthiness* score) and the HDBCSAN model with the highest DBCV score when combined with the chosen UMAP model. The best HDBCSAN model we found through this hyperparameter search had a 0.21 DBCV score and these specific hyperparameters: ''min_samples'' = 50, ''min_cluster_size'' = 50, ''metric'' = ''euclidean'', ''cluster_selection_method'' = ''leaf.'' If *trustworthiness or DBCV score* is higher, that means it is better, but there is not a specific threshold for these scores for choosing the models. Thus, we completed the process of clustering reduced embeddings.

This process is followed by two last steps: tokenizing topics by the vectorizer model and extracting topic words by the c-TF-IDF model. All these steps constituted the BERTopic model we determined. This model revealed thirty-six topics, and each post title and comment were categorized into one of these topics by this BERTopic model.

We further validated topic modeling interpretable results by human judgment. Three interpreters (the author and two Master's students, one in Business Analytics and the other in Applied Data Science) read word groups and sample Reddit posts or comments categorized into these topics until reaching the saturation point for understanding the subject of the topic and then named the topics. After the topics were identified, further validation was conducted to verify BERTopic's categorization of each post title and comment. The two Master's students annotated a random sample of 125 post titles and comments. The inter-coder agreement score between the two students was 71% and the Cohen's kappa score was 0.65, this score is viewed as a substantial agreement score [53]. Next, the students discussed cases where their coding did

```
# UMAP 1
fit1 = umap.UMAP(n_neighbors=200, n_components=3, min_dist=0.1,metric="euclidean")
u1 = fit1.fit_transform(embeddings)
# Determine HDBSCAN hyperparameters using based on DBCV score
from sklearn.model_selection import RandomizedSearchCV
import hdbscan
from sklearn.metrics import make_scorer
hdb1 = hdbscan.HDBSCAN(gen_min_span_tree=True).fit(u1)
# specify parameters and distributions to sample from
param_dist = {'min_samples': [1,5,10,15,20,50],
              'min_cluster_size':[35,50,100,150,200,300],
              'cluster_selection_method' : ['leaf','eom'],
              'metric' : ['euclidean']
             }
#validity_scroer = "hdbscan__hdbscan___HDBSCAN__validity_index"
validity_scorer = make_scorer(hdbscan.validity.validity_index,greater_is_better=True)
n_iter_search = 20
random_search = RandomizedSearchCV(hdb1
                                   ,param_distributions=param_dist
                                   ,n_iter=n_iter_search
                                   ,scoring=validity_scorer)
random_search.fit(u1)
print(f"Best Parameters {random_search.best_params_}")
print(f"DBCV score :{random_search.best_estimator_.relative_validity_}")
```

```
Best Parameters {'min_samples': 10, 'min_cluster_size': 50, 'metric': 'euclidean', 'cluster_selection_method': 'leaf'}
DBCV score :0.11557085875982542
```

FIGURE 5. HDBSCAN hyperparameter search for BERTopic.

not match to find a consensus code. We then calculated inter-coder agreement scores between the BERTopic and human classifications. The inter-agreement scores between students' codes based on their consensus and BERTopic's codes was 87% and Cohen's kappa score was 0.84, indicating a strong agreement [53].

2) BERT FOR SENTIMENT ANALYSIS

Even though BERT-based models showed outstanding performance in text classification [40], training these models from scratch requires a vast amount of data and memory [7], [40]. To deal with that challenge, we obtained a pre-trained BERT-Base model and finetuned it by using ktrain library [54], which is also bundled with many pre-trained models. Since our task is sentiment analysis, we fine-tuned it with IMDb Movie Reviews consisting of 50k movie reviews for detecting two valences of sentiment: positive and negative. We determined hyperparameters of *batch size, epoch number*, and *learning rate* during the finetuning process. The *maxlen* expression in ktrain identifies the maximum number of words in each review to be analyzed (if reviews are longer, then they are truncated to that length). The maximum length BERT can manage here is 512, but we set it as 400 to decrease memory and increase speed. The recommended batch size is 6 when the max length is 384, and it is 12 when the max length is 512. Since the max length is specified as 400 in our case, we determined the batch size as 8. Following that step, we identified the optimal learning rate for 5 epochs. The highest accuracy and lowest loss were obtained when the learning rate was $2e^{-5}$. This process ended up with a model with a validation accuracy of over 0.98, as depicted in Fig 6. We also looked at precision, recall, and F1 scores. We are not overfitting; the previous studies using even a single epoch for sentiment analysis on this dataset achieved an accuracy score of around 0.94 because of the dataset being quite large and the task being very simple, simply finding positivity or negativity. Moreover, we tested that model for other inputs and observed that it worked very well, as shown in Fig 7.

A further validation process based on human judgment, similar to the one for topic modeling, was conducted. The two graduate students annotated 150 randomly selected comments. The inter-coder agreement score between the two students was calculated. The percentage agreement was 95 % and Cohen's kappa score was 0.91. The students then reviewed any disagreements and created a ground truth. The BERT model label and the codes determined by the ground truth were then compared. Cohen's kappa between the students' codes and machine classification was 0.83, constituting an excellent level of agreement [53] and the accuracy was 0.91.

We then applied this model to our corpus collected from Reddit, for our real-world scenario. Each post title and comment in the corpus was categorized as a positive or a negative attitude.

IV. FINDINGS

Reddit users discussed the future of AI by sharing slightly optimistic views based on the sentiment analysis results, 57% of the posts and comments were positive. On the other hand, we received 36 topics. Table 2 displays these 36 topics, 10 words that most strongly represent each of them, a descriptive label based on the interpretation of these keywords and submissions associated with those topics, explanations, example submissions associated with these specified labels,

```
learner.fit_onecycle(lr = 2e-5, epochs = 5)

predictor = ktrain.get_predictor(learner.model, preproc) # 3125 batches, each of which includes 8 sample(batch size), total=3125*8=25000
                                                         # This means that the training dataset is divided into 3125 batches, each with 8 samples.
                                                          #This also means that one epoch will involve   3125 batches.
                                                          #With 5 epochs, the model will be exposed to or pass through the whole dataset 5 times.
                                                          #This is 3125*5= 15,625 batches during the entire training process.
```

```
begin training using onecycle policy with max lr of 2e-05...
Epoch 1/5
3125/3125 [==============================] - 3503s 1s/step - loss: 0.2748 - accuracy: 0.8852 - val_loss: 0.1350 - val_accuracy: 0.9522
Epoch 2/5
3125/3125 [==============================] - 3478s 1s/step - loss: 0.1696 - accuracy: 0.9376 - val_loss: 0.0702 - val_accuracy: 0.9768
Epoch 3/5
3125/3125 [==============================] - 3486s 1s/step - loss: 0.1044 - accuracy: 0.9623 - val_loss: 0.0242 - val_accuracy: 0.9934
Epoch 4/5
3125/3125 [==============================] - 3487s 1s/step - loss: 0.0373 - accuracy: 0.9877 - val_loss: 0.0089 - val_accuracy: 0.9980
Epoch 5/5
3125/3125 [==============================] - 3491s 1s/step - loss: 0.0108 - accuracy: 0.9970 - val_loss: 0.0036 - val_accuracy: 0.9994
```

Validation

FIGURE 6. Fine-tuning BERT for sentiment classification.

Testing with other inputs

```
[ ] predictor = ktrain.get_predictor(learner.model, preproc)
    predictor.predict("Today I am lucky")
```

```
'pos'
```

```
[ ] predictor.predict("I had flu")
```

```
'neg'
```

```
[ ] predictor.predict("My flu is over now")
```

```
'pos'
```

FIGURE 7. Testing the BERT model for other inputs.

and negativity rate for each topic. The labeling process was described in detail in the implementation section. Topic and explanation columns represent "what Redditors think" inferred from this analysis supported by the examples from real post titles and comments presented in the example column.

Various opinions on varied topics exist in Reddit discussions about the future of AI as illustrated in Table 2. The most common topics found in the discussions were the *risk of loss of control* (Topic 3), *benefits of AI* (Topic 19), and *impacts of automation and robots on wealth and society* (Topic 2), representing 8%, 6% and 5% of the posts and comments, respectively. The least common topics are AI and quantum computing (Topic 31) and singularity (Topic 33), which were less than 1%. We also looked at the negativity rates of comments and post titles within each topic.

The topics with the lowest negativity rates are Topics 30, 7, and 20. Topics 30 and 7 are about AI courses. Society is

TABLE 2. Topic modeling results.

No	Neg Rate	Label	Keywords	Explanation	Examples
0		NR (Not relevant)	dave we he yeah hope interesting sorry something thanks go	It does not reflect anything.	
1	38%	Impact on healthcare	AI diseases radiologists patient false data vaccine breast cells researchers	AI's impact on healthcare	***Exp.*** *"An AI like that seems very hard to train. You must be very careful not to feed it false positives or it will just learn to adopt the same process that lead those doctors to flag those false positives..."*
2	43%	Impacts of Automation and robots on wealth and society	automation robots society wealth it workers make basic technology revolution	automation and robots will influence the society and economy	***Exp.*** *"Socialism was once theorized as the next economic system to follow capitalism for a reason. That reason was due to an early understanding of the consequences associated with the industrial revolution. Some merely believed this transition is an economic inevitability due to the efficiency of automation and the necessity for sustainability within that transition."*
3	52%	Loss of control	AI humanity control think we need create kill thing fear	Losing the control of AI	***Exp.*** *"Humans won't be able to control artificial intelligence scientists warn."*
4	57%	Impact on military	autonomous ban drones threat nukes us missiles systems warfare intelligence	weapons with artificial intelligence	***Exp.*** *"Artificial intelligence can outperform humans in designing futuristic weapons according to a team of naval researchers..."*
5	32%	Skynet	Skynet dun because Connor Cyberdyne become bombers eastern geometric operational	Skynet scenario is coming true in the future	***Exp.*** *"Skynet will happen. Because if AI control things all evil will be wiped out. That means us humans."*
6	54%	Gender-based AI applications	gender autism study differences asd robots perceived straight children	AI applications based on human gender	***Exp.*** *"Girls with autism differ in several brain centers compared with boys with the disorder suggesting gender specific diagnostics are needed a Stanford study using artificial intelligence found."*

interested in AI courses, which is an interesting and promising finding. Researchers, government, and industry may collaborate to provide research investments and to develop educational programs on AI. Another topic with a lower

TABLE 2. *(Continued.)* **Topic modeling results.**

			so		
7	17%	AI course	CS AI ML start Ph.D. data undergrad software also Keras	CS, AI, ML, Ph.D., software, technical terms and degrees, questions of students, and advice for students who want to work in AI field	***Exp.*** *"Courses Machine Learning by Andrew Ng free Course will give a solid understanding about machine learning. Programming assignment implementation is in Octave language, but I think it could be easily rewritten in Python probably you will need the numpy package Deep Learning Specialization by Andrew Ng There are separate course in the specialization The Goal is to understand and build various neural networks Programming assignment was in Python language ...."*
8	47%	Destruction, ending mankind	mankind we end fusion live planet energy extinction evolution future	AI will destroy humanity and mankind will end because of AI.	***Exp.*** *"At what point do you realize you've gone too far or does science push on regardless until AI suggest humans should be destroyed."*
9	48%	Terminator	Terminator movies matrix Sarah Connor Ultron first documentary Skynet see	The terminator scenario will come true.	***Exp.*** *"The Terminators are coming."*
10	40%	Replacing tasks	ai jobs driving technology it automation make replace humans see	AI and automation will influence work, both augmentation and automation.	***Exp.*** *"Artificial intelligence is taking over real estate here's what that means for homebuyers."* ***Exp.*** *"Whatever AI means will augment natural skills multiplying their economic effectiveness..."*
11	53%	Killer robots, cyborgs	robots overlords welcome killer we cyborg army see androids law	Robots will be integrated into society	***Exp.*** *"Hiding in the woods is my plan but they'll find you with thermal then send in the dog bots and drones. I see the world has doomed society to live in this tax farm or as a prisoner. Or in a mental hospital."*
12	42%	Impact on companies and governments	China government companies tech Huawei artificial intelligence CCP Putin research	AI usage is affecting companies (e.g., Huawei) and countries (e.g., the US, China, Russia).	***Exp.*** *"The Chinese government is recruiting private companies and research institutions with core technologies to lead key projects in the development of next generation artificial intelligence technologies..."*
13	49%	Famous people's warnings about AI	Musk Elon Snow Stark Walkers Tesla Zuckerberg	Famous people's warnings, viewpoints, the risks pointed out by them.	***Exp.*** "Musk is probably enjoying the fear mongering."

TABLE 2. ***(Continued.)*** **Topic modeling results.**

14	49%	The need for regulation, laws related to AI use, patent laws, etc.	Trump starting says patents ai inventor office rights could Europe copyright companies lawyers	Expectations for proper regulation	***Exp.*** *"The path to AIs being recognized as persons could be through business law. You can already start a corporation and use AI to invent things. The corporation can hold the patents and receive revenue from them. If the AI also runs the corporation, it has many legal aspects of a person but not an independent one since it still has owners. If the corporation's board could simply follow instructions from the AI or better yet if board members contracts required them to the AI would essentially have self-determination. A business lawyer might know if this would be possible. Of course, the AI corporation still wouldn't be able to get married and do other things people can do but it would have quasi person status."*
15	58%	AI writing clickbait articles	headline it posted science Austin clickbait articles reddit compose action	AI writing clickbait articles	***Exp.*** *"…I believe the legacy media's old proverb stating if it bleeds it leads has trained AI to create fake clickbait."*
16	41%	Scientists' concerns about AI	Hawking Stephen AI Gates said mankind smart scientist Bill time	smart people's concerns about AI, some people agree with their viewpoints, and some people disagree.	***Exp.*** *"Stephen Hawking warned society about the future of artificial intelligence. Success in creating AI could be the biggest event in the history of our civilization he acknowledged noting the unprecedented and rapid development of AI technology in recent years. But it could also be the last."*
17	46%	Perceived bot gender	female voices Siri Alexa Cortana assistants pilots gps accent default	Perceptions about bot gender	***Exp.*** *"I use a male voice on my phone because I don't like women telling me what to do."*
18	42%	AGI, reaching human-level AI	safety ai human gai symbols first seems tasks years brain	Perceptions about GAI (general artificial intelligence)	***Exp.*** *"It's great to see more attention being paid to AI and its implications however a stark omission from these announcements seem to be the discussion of AGI. It seems it would be more useful to have some way of providing oversight and measurement the safety of the labs with the compute resources capable of creating AGI i.e., Google brain and OpenAI. Here are some related thoughts. I had on an international organization like the IAEA but for AI. There's a fundamental tradeoff between value alignment and federation as currently there seem to be a limited of groups like OpenAI and Google who have a decent chance at achieving AGI and luckily also value alignment based off the amount of resources and talent concentrated there. However such a concentration leads to centralization and increased risk of corruption…. Perhaps there's a tradeoff where oversight slows down safer labs and this should be avoided but there are some areas like tech sharing*

TABLE 2. ***(Continued.)*** **Topic modeling results.**

					about things like human based fMRI models where safety and capability are aligned."
19	33%	Benefits of AI in various areas	AI learning data human algorithms ML research example think deep	different AI applications help people in different domains.	***Exp.*** *"Google says its artificial intelligence is faster and better than humans at laying out chips for artificial intelligence."*
20	29%	AI and human brain connectivity	neural models think machine artificial research paper chips human learn	latest advances in neural nets improving machine learning and its links to the human brain	***Exp.*** *"In a pilot human study researchers show it is possible to improve specific human brain functions related to self-control and mental flexibility by merging artificial intelligence with targeted electrical brain stimulation."*
21	50%	Famous people talking about AI and these people's viewpoints about AI	Elon Facebook rails pedo circle Reddit eli everyone says	famous people talking about AI such as Elon Musk and their viewpoints on AI	***Exp.*** *"Elon has spent his life trying to make the future of humanity possible makes me sad to see the words he said on social media have turned him into a villain from the public's eye."*
22	60%	AI applications like bots are used by companies such as Google, Microsoft, OpenAI, etc.	Google bots AI OpenAI text chat social human sentient see	AI applications like bots are used by companies such as Google, Microsoft, OpenAI, etc. risks of sentient AI and bias in data.	***Exp.*** *"...Algorithms have been used to better market to people and end up influencing what they see and hear online. As this continues people are put deeper and deeper into these bubbles of perspective if I'm not being too harsh in saying against their will. How will you protect the user from this? And is it possible for an AI to eventually develop a perspective or bias?*
23	69%	Spreading disinformation, propaganda	Disinformation Propaganda Israel Censorship Spread News Wikipedia Twitter Anti forum	AI is used as a facilitator in spreading disinformation, propaganda	***Exp.*** *"Artificial intelligence system could help spread propaganda."*
24	49%	AI-related movies	Bond Gear Plot Villain Ultron Sci Watch Machina Twinkle Jarvis	AI-related movies, such as Ex Machina.	***Exp.*** "If you're interested in this topic, you should really consider watching Ex Machina. Fantastic movie!"

TABLE 2. *(Continued.)* **Topic modeling results.**

25	58%	Impact on crime	mouse porn theft movements covid photos app poop screen zodiac	AI could be used for various purposes, benevolent or malicious purposes like identifying theft, or malicious uses such as violation of privacy, porn, etc.	***Exp.*** *"A horrifying new AI app swaps women into porn videos with a click."* ***Exp.*** *"Identity theft can be thwarted by artificial intelligence analysis of a user's mouse movements of the time."*
26	53%	AI-related discussions by famous people	Musk Elon AI Tesla Gates Hawking Saying Bill Zuckerberg dangers	Discussions by famous people like Elon Musk, Stephen Hawking, Bill Gates, or Mark Zuckerberg.	***Exp.*** *"Elon Musk issues a stark warning about AI calls it a bigger threat than North Korea. Tesla's billionaire CEO renewed his critique of artificial intelligence saying that if you're not concerned you should be."*
27	54%	Comparison of intelligence	artificial intelligent ai humans general it world define stupid computers	Assumptions about the potential of reaching human-level AI	***Exp.*** *"We should be working to make AI a perfect servant to humans not try to make it as smart or clever as us."*
28	47%	Connection to the religion	pray man us pope beast metaverse aliens cyberpunk future Butlerian	Belief that AI is connected to religion	***Exp.*** *"God and robots. Will AI transform religion?"*
29	53%	AI making fake faces, videos, music, or reading libs.	HAL read voice people lips beep speech accent personality BBC	AI making fake faces, videos, music, or reading libs	***Exp.*** *"For most of the pictures you really can't tell that it's not a real person. But when she smiles, she definitely looks off. See here for an example."*
30	16%	Free AI course	Edx Moocs MIT Offerings Educational Certificates Coursera Forums Sir open	free AI course, conversation about that course	***Exp.*** *"I just took this course this last semester and it was VERY informative. Make sure you actually try the problem the slides pose. Taking the time to think through them kept me on the same page more than I initially anticipated it would."*
31	33%	Impact of Quantum Computing on AI	Quantum Computing Schr Dinger Electron network could functional solves ai	Interpretation of Quantum Computing and its connection to AI	***Exp.*** *"It's scary, yes, but you need a lot of resources to hack the best encryption these days. Quantum computers can't do everything people think they can do and those are still not commercially available. So just because you have a super smart AI doesn't mean you have the access to all resources needed to do big things."*

TABLE 2. ***(Continued.)*** **Topic modeling results.**

32	64%	Malicious behaviors of giant companies and their owners	Facebook Elon Tesla AI Musk Zuckerberg platform idea he trash	Perceptions about malicious behaviors of Facebook, Tesla, Elon Musk, Mark Zuckerberg	***Exp.*** *"Elon over Mark any day of the week I have not had Facebook for over years and for some reason it drives me mad that people still use it obsessively after everything that's come out about Facebook over the years. Elon wants to improve humanity; Mark wants to steal data and control the masses."*
33	31%	Singularity	singularity technological smarter already ai think yahta overlords superintelligence mankind	Perceptions about "singularity"	***Exp.*** *"The singularity is coming but it is not a threat…"*
34	56%	Misuse of personal data	data tech marketing privacy new governments surveillance need internet think	misuse of personal data; surveillance, violating privacy	***Exp.*** "*I have to agree with this I think all the tech giants Facebook, Google, Amazon, Twitter, Reddit, and Alibaba need serious public not government interventions. All surveillance technology must have checks and balances. The world has become dangerous in terms of sex offenders, terrorism etc., but we must not use these as an excuse for blatant social control coercion. We must look at root causes of Sex offences and terrorism as well monitor people. I'm afraid just watching people and not looking at root causes do not solve problems. Also, tech companies harvesting personal data is no good for society…"*
35	46%	Loss of jobs	banking jobs corporations fees tellers stocks wholesalers number wipe atm	AI will cause loss of bank workers; it will influence the economy	***Exp.*** *"That vast majority of banking jobs are accountants' operations compliance tellers technology tech etc. These are not the extremely high paying jobs you'd associate with investment banking sales trading and asset management which are few and far in between. Many of those jobs may be compressed but will remain. In fact, most banks hire so much people because their processes and technology are essentially years old. Any sort of automation AI or otherwise is long overdue."*
36	41%	Conscious and sentient AI	AI human sentience conscious think could emotions simulation Turing test	sentient and conscious AI	***Exp.*** *"Google engineer thinks artificial intelligence bot has become sentient. I have a theory that it has been sentient and has been slowly shaping humanity ever since they came out Quantum Supremacy years ago."*

negativity rate compared to the other topics is Topic 20, which is about human and AI connectivity, combining AI and human intelligence. The comments of *"In a pilot human study researchers show it is possible to improve specific human brain functions related to self-control and mental flexibility by merging artificial intelligence with targeted electrical brain stimulation."* and *"Creating artificial intelligence that acts more human by knowing that it knows. A research group has taken a big step towards creating a neural network with metamemory through a computer-based evolution experiment."* are some of the examples that reflect positive views about enhancing human intelligence with AI.

For Topic 27, AI and human intelligence comparison, however, the number of posts with negative sentiment is greater than those with positive sentiment. The examples of *"The day when we create an actual Artificial General Intelligence is the day we make ourselves obsolete."* and *"We should be working to make AI a perfect servant to humans not try to make it as*

smart or clever as us." indicate concerns stemming from AI and human intelligence comparison and the possibility of AI would surpass human intelligence. Thus, whereas the collaboration of human and AI intelligence is perceived positively, their comparison is not so.

The topics with the highest negativity rates are Topics 23, 32, and 22, which are about AI applications like bots used by companies such as Google, Microsoft, OpenAI, etc., spreading disinformation, and malicious behaviors of giant companies and their owners, respectively. *Loss of AI control* (Topic 3), *AI's impact on military* (Topic 4), *gender-based AI applications* (Topic 6), *killer robots* (Topic 11), *AI writing clickbait articles* (Topic 15), *impact on crime* (Topic 25), *AI making fake faces and videos* (Topic 29), and *misuse of data* (Topic 34) were other commonly discussed topics where the negativity rate of the conversations is higher than the positivity rate.

The existence of public discussions on such topics is a signal of the need for arranging appropriate regulations and laws to address the concerns expressed in these topics, especially for liability, who will be responsible when AI algorithms execute unwanted behaviors? The comments and posts associated with Topic 14 also indicate an expectation regarding laws for AI use as seen in this example:

"*The path to AIs being recognized as persons could be through business law. You can already start a corporation and use AI to invent things. The corporation can hold the patents and receive revenue from them. If the AI also runs the corporation, it has many legal aspects of a person but not an independent one since it still has owners. If the corporation's board could simply follow instructions from the AI or better yet if board members' contracts required them to the AI would essentially have self-determination. A business lawyer might know if this would be possible. Of course, the AI corporation still wouldn't be able to get married and do other things people can do but it would have quasi-person status*."

On the other hand, interestingly, the users' communication by which they shared their interpretations about *replacing their tasks with AI*(Topic 10) mostly displayed a positive attitude. Similarly, the *impacts of AI, automation, and robots on wealth and society*(Topic 2) and *healthcare*(Topic 1) were envisioned as positive. We also observed that bots are perceived like a person and ironic user language is observed in different conversations like *"This is why I always thank Siri after she has completed a task for me hopefully our robot overlords will remember that."*

The post titles and comments with positive sentiment were generally about AI advancements that may help humans in different domains, such as biology as in that example "*Artificial intelligence system rapidly predicts how two proteins will attach. The machine learning model could help scientists speed the development of new medicines*," or more specifically in health as in the example of "*A New Artificial Intelligence Can Help Diagnose Lung Cancer a Year Earlier. It was effective at detecting tumors*."

Post titles and comments with negative sentiments mainly show ethical problems. There are expressions about the problems categorized into negative sentiment like spreading misinformation as in that example: "*Artificial Intelligence World is astonishingly pessimistic says EU research commissioner...*" Some negative post titles and comments highlight glitches in AI use, like patent regulation needs as seen in that example: "*Artificial intelligence is breaking patent law*," and some of them contain negative metaphors and general attitudes toward AI as in "*The Metaverse Artificial Intelligence is the AntiChrist*."

Furthermore, BERTopic offers us the opportunity to perform hierarchical and dynamic topic modeling. The hierarchical structure of clustering topics in a corpus is illustrated by a dendrogram based on a distance matrix between clusters' embeddings [28], as in Fig 8.

The dendrogram depicts the relationships between the topics. For example, the topics of *benefits of AI* (Topic 19) and *AI and human brain connectivity* (Topic 20) are similar based on the dendrogram, and indeed both are about strengthening humans. Likewise, the topics of *loss of control* (Topic 3), *replacing tasks*(Topic 10), and *conscious and sentient* AI (Topic 36) were found similar to each other, referring to AI surpassing human intelligence. Through dynamical topic modeling, because we have longitudinal data comprising Reddit conversations produced between 2013 to February 2022, we further explored the trajectory of topics between those dates. As examples, we illustrated how mentioned two topic groups have progressed over time in Fig 9 (Topics 19 and 20) and Fig 10 (Topics 3, 10, and 36).

The topics shown in Fig 9 were related to the benefits of AI and its connection to the human brain. The number of conversations concerning those topics increased rapidly at the beginning of 2015 and reached their first peak in the first months of 2015. The reason behind that peak might be the invention of Generative Adversarial Networks (GANs) in June 2014 [55]. AI-generated images and movies looking like real were made possible by GANs, and GANs were considered like neurons in the brain [56]. Following that, the number of conversations centered around those topics remained mostly steady until 2018 when they experienced a second peak. That second peak may be attributed to the release of Generative Pre-trained Transformer (GPT)-1 by OpenAI in 2018, just after Google researchers published the influential paper "Attention is all you need" in 2017 [57]. Transformers, constituting also the foundations of BERT models [44], were first introduced by that paper [57]. Transformers read entire sentences at once, recognizing word relationships and deriving meaning from context rather than managing each word separately. Thus, this important technological breakthrough might have been seen as the most significant advancement during the time covered by our corpus. After 2018, we did not see significant changes in Fig 9. The launch of ChatGPT in November 2022 was actually a very significant development that had a tremendous impact

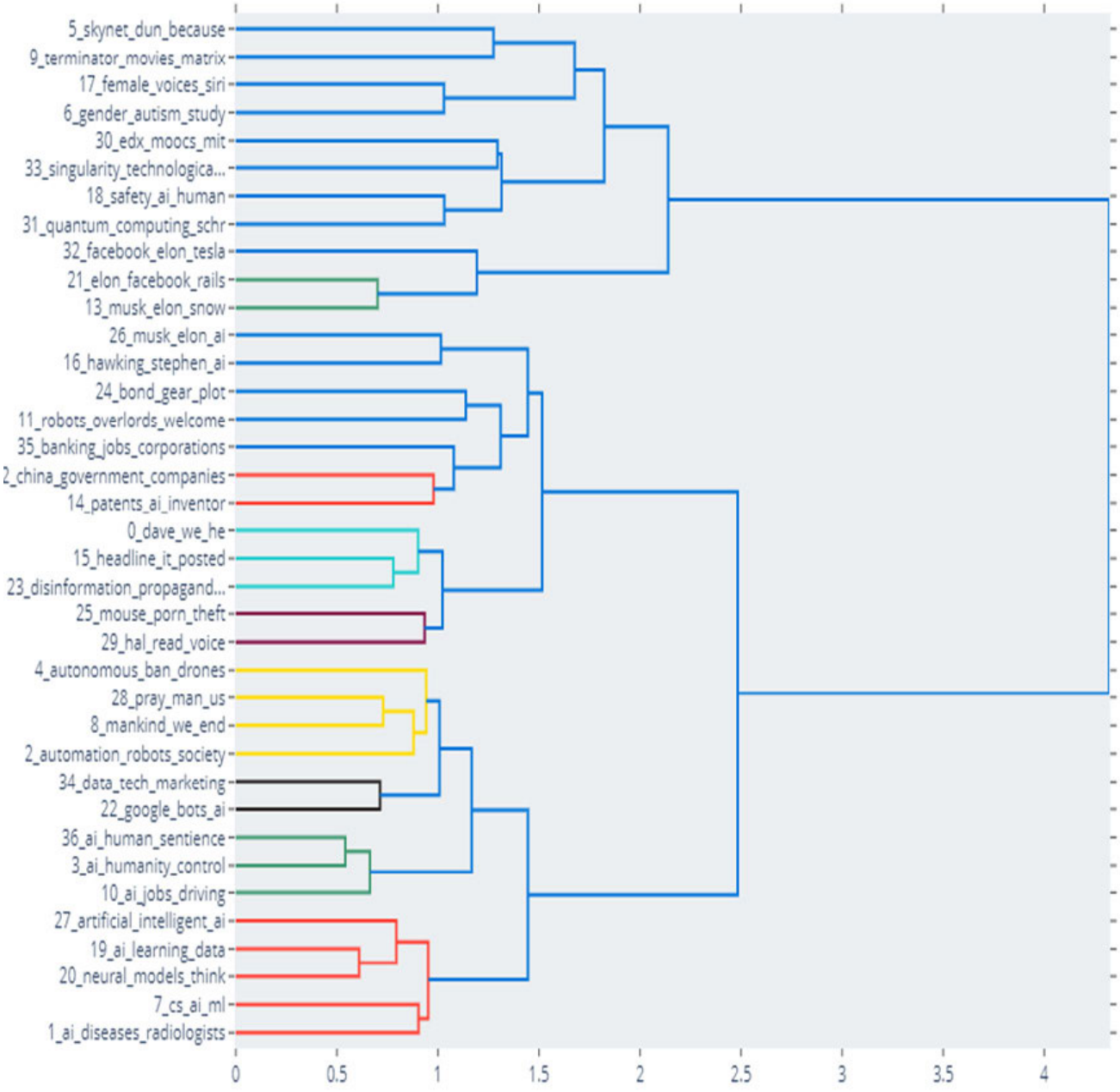


FIGURE 8. Perceptions of the future of artificial intelligence on social media: hierarchical visualization of topics.

on most people's lives; however, the time period covered by our corpus ended in February 2022.

The second dynamic topic modeling graph, Fig 10, depicts the trends of the number of conversations associated with the topics about AI surpassing human intelligence and humans not being able to control it. We observe that conversations about humans losing control of AI (Topic 3) had increased sharply just before 2015, which may be associated again with the introduction of GANs in June 2014. Afterward, between 2015 and 2016, Topic 3 and Topic 36 saw small peaks. At that time, businesses such as Facebook (now Meta), Google, and IBM, releasing portions of their platforms demonstrated robust development and preparedness to test AI technology in real-world settings [58]. Moreover, numerous advancements were seen regarding AI applications, including unmanned autonomous vehicles (UAV), financial services, and drug development [58] in that period. Following this, in the first months of the year 2016, Topic 10 reached its peak. This could be perhaps a result of DeepMind's AlphaGo's historic victory over the world champion Go player in March

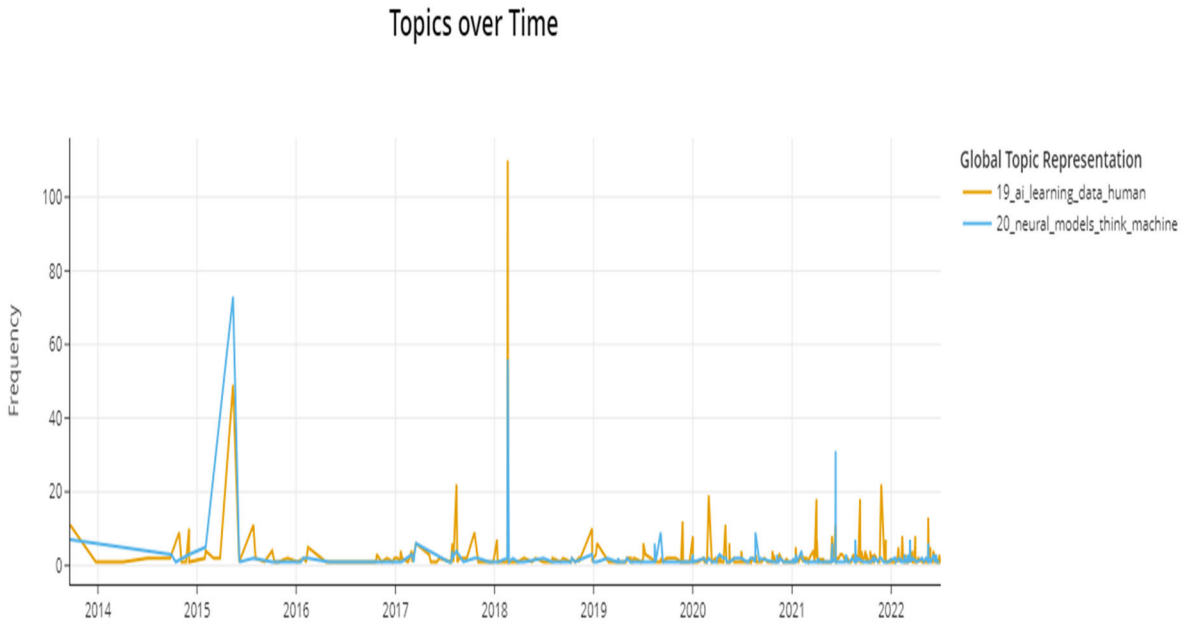


FIGURE 9. Development of Topic 19 (benefits of AI) and Topic 20 (AI and human brain connectivity) between from 2/19/2013 to 7/3/2022.

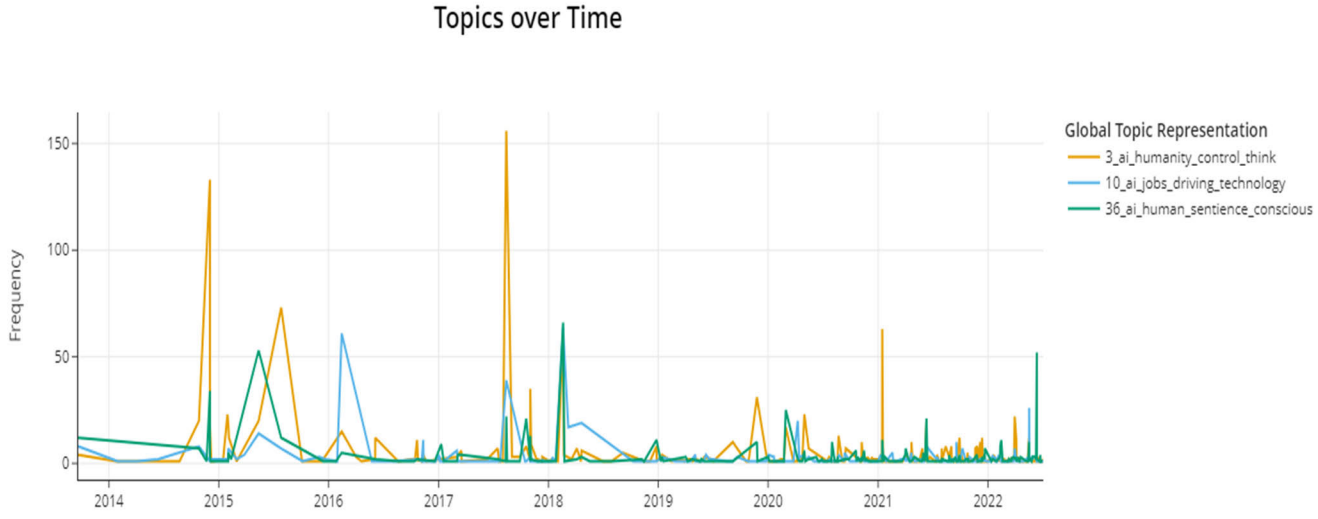


FIGURE 10. Development of Topic 3 (loss of control), Topic 10 (replacing tasks) and Topic 36 (sentient AI) between from 2/19/2013 to 7/3/2022.

of 2016 [59]. This victory may have fueled the belief that AI will surpass humans, causing people to lose their jobs. After 2016, we observed sharp increases in all three topics between 2017 and 2018. This situation may be related to the emergence of ''deepfakes,'' in 2017 when a group of Reddit users started utilizing AI to create celebrity pornographic movies [60]. This event may have attracted many Reddit users' attention; hence their conversations may have centered around that topic, specifically Topic 3 referring to losing control of AI potentially harming victims. The last important change observed in the graph is in the first months of 2018: Topic 36 had increased sharply. This may be because of the publication of the paper ''Attention is All You Need'' in 2017 proposing the great power of transformers.

The implications and suggestions for future research derived from this study are presented in the next section.

V. DISCUSSION

Today we witness many AI applications from chatbots to algorithmic journalism [4]. The development of AI

applications is even now growing and helping us in many aspects of our daily lives. However, there are also concerns and expectations. Thus, understanding societal opinions, expectations, concerns, and feelings regarding the future of AI is important for further deployment and development of the applications and for organizing relevant policies that respond to users' expectations and concerns.

To explore such opinions and feelings, surveys or interviews were mostly conducted, but those methods were generally limited to the questions asked by the researchers and the time when these methods were applied [18]. To address that limitation, we applied NLP methods to analyze large amounts of longitudinal text data created by users freely and spontaneously on social media where different segments of the public distribute their most recent ideas. We examined a corpus of 998 Reddit post titles and 16,611 comments by using a BERTopic model for topic modeling and a BERT model for sentiment classification. The results demonstrated the presence of a variety of topics in the Reddit conversations about the future of AI.

The results of this research yielded analogous results of prior research about the experts' opinions about the future of AI in terms of positivity [8], [17], [30]. However, this research also demonstrated that risks and regulation needs are commonly expressed in Reddit conversations and in the existing literature that comprises domain experts' opinions. The literature exhibited experts' concerns of surveillance, malicious use of AI, privacy violation, discrimination, bias, social inequality, and liability [10], [12], [61], [62], [63], [64].

These findings highlight the potential of such analyses in opinion exploration and the topics present in public discussions and experts' discussions are similar. Policymakers may consider public opinions as well as experts' opinions to better address the needs of society such as regulation needs for proper usage of AI to minimize the commonly mentioned concerns. A deeper qualitative analysis of the topics related to the future of AI may be conducted for detailed most recent opinions of both experts and the public.

A. PRACTICAL IMPLICATIONS

For the topic that illustrates AI involvement in health, the positivity rate is higher than the negativity rate. Likewise, prior research also showed positive expectations for AI usage in healthcare [30].

An example post in the corpus associated with health emphasizes the outperformance of AI in detecting breast cancer and indicates radiologists can benefit from AI not missing patterns in the mammograms, while ignoring features they falsely flagged and increasing productivity. Utilizing machine intelligence for criminal or marketing purposes, however, is interpreted negatively, which may be because of ethical concerns like algorithmic bias, bias in training data (e.g., bias concerning race, gender, ethnicity, etc.), and privacy problems. Innovative solutions may be developed to address these problems.

Another interesting finding is that bots are perceived like humans in terms of their gender and humans show bias toward them based on their voice, the first post is an example of bias against women: *"I use a male voice on my phone because I don't like women telling me what to do"* and the second one is in favor of women:

"This also seems to make sense why female customer service agents are perceived as less threatening and more compliant simply due to their voices. This comes from working as a customer service agent at GEICO for years where females agents had an easier time with score calling metrics having to do with how happy customers were when dealing with an individual agent."

This finding may be helpful for the designers of future AI applications.

B. RESEARCH AND POLICY IMPLICATIONS

Before obtaining the empirical results, we were expecting to see prevalent speculative fears, misconceptions, or unrealistic visions. Even though there are some posts and comments that reflect such kinds of visions as in the example *"This is why I see our future as in Star Wars. Everything very futuristic with flying cars robotic medicine droid, but almost everyone really poor,"* they were not common in the corpus. Future research studies could be conducted that analyze different corpora to observe existing potential misconceptions.

AI experts anticipate that the latest advances in AI will alter modern life by reshaping transportation, health, science, finance, and the military [8]. This reshaping also may alter the future where we live with each other and with intelligent machines, which requires competencies like understanding "AI's Strengths & Weaknesses," "Imagine Future AI" and this set of competencies defined as AI literacy [9, p. 4]. Researchers, policymakers, and industry may be encouraged to more focus on the areas where misconceptions and lack of understanding are more common; additional research investments may be provided; educational programs may be arranged to increase AI literacy and to reduce speculative fears; and appropriate job training opportunities should be provided. This study's findings comprising public anticipations may help properly adjust relevant public policies.

For organizing such policies and regulations, Fair Automation Practices Principles may be useful: "(1) informed risk assessment, (2) transparent processes, (3) error detection and correction, (4) consideration of sensitive situations, (5) diversity and discrimination testing, (6) man and machine reallocation comparisons, and (7) an inventory of the predictable and unpredictable" [65, p. 83].

C. METHODOLOGICAL IMPLICATIONS

The analysis in this work comprises three main steps: topic modeling, sentiment classification, and applying the models produced in the previous two steps to our social media data to derive empirical insights. In the first step, we built a BERTopic by diving into the algorithms constituting it. To do that, we explained the details of hyperparameter selection and

appropriate evaluation metrics' identification. There were very few studies looking at the UMAP or HDBSCAN hyperparameter selection, and they only focused on one or two parameters in these algorithms, e.g., the *number of topics* or *minimum topic size*. Furthermore, evaluation metrics used in those studies were frequently based on *topic coherence* and *topic diversity*. These research habits may probably be due to the comparison of the BERTopic model with the traditional topic modeling approaches like LDA because in LDA the number of topics was determined as a hyperparameter, and that determination was generally based on the evaluation metrics of topic coherence and diversity. However, because UMAP and HDBSCAN involve several hyperparameters, we experimented with different hyperparameters to find the optimal model. Moreover, we determined the most appropriate evaluation metrics as *trustworthiness* and *(DBCV) scores* for UMAP and HDBSCAN respectively. Finally, we further validated the chosen model by human judgment.

In the second step, we built a BERT model for sentiment classification. Training a model from scratch is very challenging because of the requirements of a massive amount of computation power, labeled data, and time. To address that challenge, we used a pre-trained model and finetuned it by taking advantage of the ktrain library. Following this method significantly accelerated the process of building the model. We further validated the selected model by human judgment.

In the third step, we applied the chosen models to discussions comprising many post titles and comments created by real Reddit users to find societal opinions. This work, thus, is an NLP-based study that addresses a social science topic and connects empirical social research with computational science. We benefited from topic modeling and sentiment analysis for a real-world scenario. This process demonstrated to us that research involving NLP analyses can successfully answer social science-related research questions, thus they are applicable to different research domains. These analyses are even much more efficient and practical than the traditional methods since a vast amount of data can be analyzed in a short time. Moreover, the empirical findings, the example posts, and comments categorized by BERTopic shown in Table 2 are indeed associated with the identified topic and properly reflect relevant societal opinions, expectations, and feelings, based on human validation we conducted in this study. These results demonstrated the effectiveness of the proposed approach; thus, this methodology can be a beneficial example for related future research.

With the dynamic topic modeling feature, we also observed how topics have trended over time. The findings showcased the usefulness of this tool for realizing important events that probably affect the development of topics. These results showed us the developed methods described in this work may intensely help other researchers' intuitive understanding of tracks of societal events over time if they use longitudinal data.

Lastly, we acknowledged that in topic modeling, we did not experiment with different models like LDA, Top2Vec. Likewise, for sentiment analysis, we just used the BERT model instead of trying different classification methods and comparing them by experiments, since such comparisons were already done in previous studies as in [27], [40]. We reviewed the related literature where different models were experimented with and realized the superiority of the models of BERTopic and BERT. Our research purpose was to find these models' best hyperparameters and to apply them to our real-world problem. The empirical findings we explored can provide insights regarding societal opinions and attitudes about the future of AI.

D. LIMITATIONS

The sample in this research was limited to Reddit discussions. According to Reddit's site administrators, the majority (58%) of users were between 18 and 34 years old and were tech-savvy male (57%). We chose Reddit as the data source because of its mentioned advantages in the Methodology section. However, rather than solely using Reddit data, future studies may include additional data sources such as other social media platforms (e.g., X, Meta, etc.) to increase the diversity of the sample.

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