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Sentiment Analysis of Public Opinion on the Internet of Things (IoT) Through Social Media

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ABSTRACT

Social media offers a timely lens into public perceptions of emerging technologies. To assess public opinion on the Internet of Things (IoT), we analyzed a corpus of 824,845 IoT-related posts collected from X between 2013 and 2022. Using Latent Dirichlet Allocation (LDA), we identified seven primary themes of discussion: Smart Home, Business Intelligence, Artificial Intelligence, Smart City, IoT Usage, Emerging Technologies, and Blockchain. We then applied an unsupervised machine-learning technique to evaluate sentiment toward each theme. Overall, public discourse was positive: 46.78% of tweets expressed positive sentiment, 43.41% were neutral, and 9.81% were negative. Although predictable, short-term shifts in tone occurred around specific events, interest in these themes remained consistent throughout the study period. These findings suggest that the Internet of Things is generally perceived favorably and demonstrate how large-scale social media analytics can capture authentic, real-time attitudes toward complex technologies. By linking public opinion to specific topics of discussion, our results provide valuable insights for researchers, policymakers, and product teams seeking to align IoT development with societal expectations.

Keywords— Sentiment Analysis, Social Media Analytics, Topic Modeling, Internet of Things (IoT).

1. Introduction

The development of social computing has brought about a new wave of socio-technical change by altering how people interact with goods, services, and organizations. Nowadays, a vast amount of information is generated by social media users [1]. Social media's explosive growth has changed the way data is produced, disseminated, and used, which has impacted organizational practices and innovation in a variety of sectors [2]. Millions of users can share their thoughts on anything from commonplace experiences to worldwide technological trends on platforms like X (formerly Twitter). Researchers now have never-before-seen chances to examine vast amounts of data and glean insights into the attitudes and actions of the general public thanks to the resulting stream of user-generated content [3]. Social media is now a vital tool for comprehending societal trends because of its transparency, diversity, and real-time cadence.

Simultaneously, the Internet of Things (IoT) has become a paradigm shift that links physical objects through networks and services, enabling seamless object-to-object communication. This extends from smart cities and homes to industrial systems and public health alerts [4, 5]. Efficiency improvements, more individualized services, increased inclusivity, and wider economic empowerment are all anticipated outcomes of this change [6]. However, public perception—which is influenced by social media discourse—plays a critical role in the diffusion, adoption, and regulation of IoT technologies as they become more and more integrated into daily life.

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Today, the main challenge lies not in data collection but in the effective analysis of large volumes of structured and unstructured web-based textual data [7]. Therefore, it is crucial to record and analyze those perceptions.

Opinion mining, also known as sentiment analysis, offers a methodical approach to deduce attitudes and opinions that are conveyed in text in a variety of fields, including entertainment, consumer goods, and social issues [8]. The ability to recognize and analyze public sentiment contained in textual data has become crucial in a society that is becoming more and more digitally connected [9]. Deeper insights into societal perceptions and behavioral patterns are made possible by sentiment analysis, a crucial subfield of natural language processing (NLP) that uncovers people's emotions, attitudes, and opinions expressed through text [10, 11]. With an increasing focus on the way sentiments embedded in posts change over time, X has emerged as a key location for these analyses [12]. Although social media analytics and IoT research have advanced, there are still not many studies that combine these fields to look at public opinion of IoT over long time periods. Current research frequently focuses on specific subjects or time periods, which restricts our ability to see how public opinion on IoT evolves.

To address this gap, we examine a large corpus of posts about IoT that were gathered from X between 2013 and 2022. We determine the major themes in public discourse and evaluate the distribution of neutral, negative, and positive attitudes among them using topic modeling and sentiment analysis. Our study contributes to the understanding of how society views IoT technologies and provides methodological recommendations for further research at the nexus of emerging technologies and social media analytics.

The current study covers a significantly longer time span of nearly a decade (2013–2022) and analyzes 824,845 tweets over a ten-year period, allowing examination of long-term stability and evolution in public discourse, allowing an examination of both the evolution and persistence of public discourse surrounding the Internet of Things, in contrast to Bian et al. (2016), which was limited to short-term, early-stage IoT data.

This study presents a topic-oriented analytical framework that concurrently investigates the relationship between dominant discourse themes—such as smart homes, artificial intelligence, and blockchain—and the sentiment distribution associated with each theme, whereas previous research has mostly concentrated on evaluating general sentiment toward IoT.

This work goes beyond aggregate sentiment measurement and offers a more detailed view of how public opinions of various IoT-related topics change and stabilize over time by combining topic modeling with sentiment analysis over a long-term dataset.

2. Literature Review

2.1. .1.Social Media and Sentiment Analysis

Social Media as a Data Source

In order to facilitate well-informed decision-making, social media analytics is a field of study that focuses on deriving significant insights from massive amounts of semi-structured and unstructured data produced on social media platforms [13]. Social media has grown ingrained in people's daily lives due to the ongoing development of information technology [14, 15]. As a result, the enormous and constantly growing amount of data generated on these platforms has become a useful and crucial source for scholarly research [16]. Data were collected from major social media platforms, including X, TikTok, Instagram, and Facebook [17]. X (formerly Twitter) is particularly valuable due to its openness, global reach, and highly engaged user base [3]. More broadly, social media platforms have evolved into influential marketplaces for exchanging ideas, opinions, expertise, and feedback [3, 18]. These interactions generate extensive, unstructured data, making social media analytics essential for extracting insights into user sentiments, behaviors, and emerging trends[19, 20]. Sentiment analysis makes it possible to systematically examine these data in order to identify patterns in public perceptions and behavior. The use of aspect-level sentiment analysis has grown in popularity. It finds several aspects in a sentence, gives each one a sentiment polarity, and then aggregates the findings to estimate a sentiment as a whole [21]. Compared to analyses at the document or sentence level, this fine-grained method provides deeper insight.

Sentiment Analysis: Techniques and Applications

A branch of natural language processing called sentiment analysis (SA) forecasts an entity's positive or negative polarity, revealing user attitudes, beliefs, and feelings. It gathers useful information from reviews, such as sentiment patterns for various elements of an item, particular liked or disliked features, and general sentiment toward a product or service [22, 23]. Sentiment analysis has proven to be flexible and analytically powerful in a wide range of fields. For example, [24] used online reviews to study consumer sentiments regarding food, and [25] used sentiment classification to study perceptions of traffic safety. To deal with classification indeterminacy, [26] used fuzzy-logic techniques to analyze data from X and introduced multi-refined neutrosophic sets. [27] found that Naive Bayes outperformed SVM and Random Forest. By comparing Support Vector Machines, Decision Trees, and Random Forests on real-time Twitter datasets, [28] broadened the application space and investigated sports sentiment with a focus on cricket. Building on these developments, [29] achieved good results on complex user-generated content by combining contextual representations with a dilated CNN for sentiment analysis in social IoT environments.

Challenges and Future Directions

The terrain and difficulties of sentiment analysis are mapped by early and recent surveys. Research directions and catalog limitations, ambiguity, noise, multilingual content, spam/inauthentic activity, and domain drift are reviewed later [30, 31]; see also [32, 33]. Foundational work (e.g., [34]) describes frameworks for processing unstructured text to extract patterns. Other syntheses survey sophisticated, scalable machine-learning methods for social media analytics and investigate efficacy in online-review contexts [35, 36]. The field's cross-sector relevance in markets, governance, healthcare, finance, and media is highlighted by a systematic review on Twitter/X [37].

Real-world value is demonstrated by applied research:[38] analyzes COVID-19 discourse in Brazil and the U.S (mainly Portuguese content), tracing thematic and temporal sentiment dynamics, aligning shifts with news events, and highlighting behavior specific to culture and region. [39] establishes an AI-based system for detecting cyberbullying from Twitter/X text, addressing platform safety at scale.

In a broader sense, X (formerly Twitter), which was founded in 2006 and is centered around brief posts (up to 280 characters today), has developed into a vital public communication platform and a wealth of quantitative and qualitative data. Large-scale sentiment signal extraction and analysis for social, economic, and policy insights is made possible by its global reach, sizable user base, and high engagement [40, 41].

Intersection of Social Media and IoT

There are unique opportunities to map public perceptions of emerging technologies at the intersection of social media and the Internet of Things. Social media records live, natural conversation about these technologies, while IoT provides the underlying infrastructure and use cases. By bridging the gap between technological innovation and societal response, user-generated content analysis assists researchers and organizations in identifying trends, issues, and opportunities related to IoT adoption. Furthermore, according to recent schematic reviews (e.g., [42]), combining blockchain, sentiment analysis, and IoT can improve applications like supply-chain management by offering comparative insights into intelligent systems of the future.

2.2. Internet of Things (IoT) and Public Perceptions

Technological Foundations and Applications of IoT

A key technology that provides data-driven solutions to maximize productivity is the Internet of Things (IoT) [43] . The Internet of Things (IoT) makes it possible for physical objects to communicate with one another seamlessly through sensors, wireless networks, and cloud services. While early research focused on object-level automation, IoT has expanded to accommodate sophisticated, data-driven applications due to networking advancements. Real-time communication is supported by wireless technologies, sensor advancements have produced smaller, less expensive, and more precise devices, and miniaturization has decreased the cost of hardware. When combined with GPS for accurate geolocation, these advancements have increased the global reach of IoT [44]. Based on this framework, IoT currently drives use cases in asset tracking, mobility and transportation, security and surveillance, inventory management, precision marketing, and context-aware services in both consumer and business contexts.

Sentiment Analysis in IoT Context

Recent studies apply sentiment analysis to understand public perceptions of IoT and adjacent technologies. [45] show that scaling strategies, such as increasing multi account usage while throttling per-second submissions, allow existing social-network infrastructure to scaffold large-scale IoT initiatives. Focusing on pandemic dynamics, [46] report that negative tweets on X (formerly Twitter) substantially outnumber positives and that month-to-month shifts in negativity track patient statistics. Complementing perception work, [47] review trust-computation models in IoT—direct, indirect, and hybrid—alongside known attacks, countermeasures, evaluation methods, and object-constraint effects. In content domains, [48] highlight media/entertainment use cases where sensor-derived signals (e.g., location, activity) enable personalization and new ad-revenue models. Beyond IoT per se, sentiment features have proved predictive in adjacent ecosystems: [49] attain ~88% accuracy for Bitcoin price movement, and [50] show improvements in recommender systems when sentiment is incorporated. Regarding networked infrastructure, [51] analyze 5G discourse on X and find overall optimism about IoT/AI applications, tempered by concerns over quality, cost, and misinformation.

Methodologically, work spans classical and deep approaches. [50] benchmark supervised models (multilayer perceptron, multinomial Naive Bayes, linear SVM, and majority vote ensembles) for consumer analytics; for Persian Twitter data, [52] employ deep neural networks (RNN, CNN) for supervised sentiment classification and report gains over baselines. In Persian web contexts, [53] demonstrate that their text-mining framework outperforms a multinomial Naive Bayes baseline and the only prior Persian study.

Collectively, these findings indicate that sentiment signals are informative for IoT adoption, trust, and adjacent decision-making tasks, while also underscoring the value of domain- and language-specific modeling choices.

Research Gaps and Opportunities

There are still significant gaps in the mapping of public perceptions of IoT at scale, despite the rapid advancements in technology. Predictive frameworks that categorize opinions (positive, neutral, or negative) regarding changing IoT trends and relate them to particular discourse themes are lacking in a large portion of the literature. For companies looking to clear up misunderstandings, adjust risk messaging, and match product roadmaps with user expectations, this kind of visibility is essential. Given the scarcity of traditional attitudinal data, user-generated content on platforms like X offers a primary, real-time resource. Systematic sentiment analysis of this content can surface concerns, inform public education, and guide adoption strategies. Taking advantage of these chances, the current study examines social media discourse to describe public opinion regarding IoT, paying special attention to situations in developing nations, thus influencing research and practice.

3. Methodology

This descriptive and practical study focuses on analyzing the views of people who play a key role in identifying consumer needs and market demands in the IoT industry. A total of 2,614,320 IoT-related tweets were obtained after filtering from an initial raw collection of approximately 6.2 million tweets. These tweets, which came from the English-speaking community on Twitter/X, offer a solid dataset for analyzing attitudes and trends related to IoT innovations. The goal is to assess the opinions that people on Twitter/X have about the Internet of Things (IoT). Data collection is the first step in the methodology, which is followed by data preparation. These include preprocessing tweet text to remove URLs, extraneous characters, and stop words, thereby minimizing noise that could skew the analysis. Next, trend extraction and topic modeling, specifically Latent Dirichlet Allocation (LDA), are employed to identify the primary topics associated with IoT discussions. The analysis continues with an evaluation of key terms extracted from the data. Finally, sentiment analysis is conducted to classify tweets into positive, negative, and neutral categories, offering a comprehensive view of public perceptions of IoT on social media.

Regarding the choice of methodology, supervised and semi-supervised approaches were not adopted because consistent labeled datasets covering a decade-long period of IoT-related discourse are not available. Manual annotation at this scale would be highly resource-intensive and could introduce subjectivity and reduce the reproducibility of the results.

Furthermore, zero-shot approaches and methods based on large language models were not considered suitable for this study due to their limited transparency in decision-making processes and the difficulty of ensuring output stability and temporal consistency over long time horizons. Given the longitudinal nature of the dataset, an unsupervised framework was therefore deemed more appropriate for capturing stable patterns and long-term trends in public discourse on the Internet of Things.

The Python programming language was used to process and analyze tweets gathered from Twitter/X. A widely adopted methodology in data mining, the Cross-Industry Standard Process for Data Mining (CRISP-DM), was utilized due to its prevalence across industries and its popularity among data miners. Table 1 delineates the steps involved in the data-mining process and describes the operations associated with each phase.

Data Collection and Data Preparation

For this study, an initial raw dataset comprising approximately 6.2 million tweets containing the hashtag #iot was collected from X (formerly Twitter) for the years 2013–2022, resulting in 2,614,320 rows after initial filtering. Given the unlabeled nature of the dataset, unsupervised machine learning methods were employed for analysis.After removing duplicates with df.drop_duplicates(), the dataset was reduced to 2,408,961 rows. The “date-time” column was then split into separate “date” and “time” fields using the Datetime library. To streamline computation, a 50% random sample was drawn via df.sample(frac=0.5), yielding 1,204,480 tweets.

Tweet length was profiled with len() (characters ranged from 4–957) and stored as “Text Length.” Word counts were computed with split() (range 1–161 words) and stored as “Text Words.” Most tweets were concise; posts with <10 words were considered too short for reliable topic modeling, and those with >60 words were Often spam-like. These were removed, leaving 871,142 tweets for further analysis.

Following language detection, non-English tweets were excluded. Comprehensive cleaning then removed stop words, extra characters/spaces, and URLs, and applied lemmatization. After cleaning, we retained tweets with 0–70 words (post–stop-word removal) as “Clean Text Word.” We further filtered out tweets with <5 meaningful words in “Clean Text Word,” producing a final corpus of 824,845 tweets

Table 1. Stages of Data Mining Execution based on the CRISP-DM Methodology

Stage	*Definition*
Business Understanding	Domain knowledge acquisition (consultation with domain experts; literature review; identification of indicators and criteria; conceptual model design); goal setting; problem definition; situation assessment (success factors, resources, needs, constraints, assumptions, risks, feasibility analysis, cost-benefit analysis); project planning.
Data Understanding	Raw data collection (sampling); data warehouse construction; initial data familiarization and description; data distribution analysis; initial data quality assessment.
Data Preparation	Data selection; feature selection (determining target features); record and variable refinement; data enrichment; data cleaning; data integration; data transformation; data normalization; dimensionality/complexity reduction; decisions regarding missing data; outlier detection; removal of abnormal or redundant values; data splitting (training/testing sets); final data formatting.
Modeling	Selection of modeling techniques/algorithms; parameter tuning; threshold adjustment; modeling with selected data; designing model evaluation procedures.
Assessment	Model evaluation; testing error evaluation; result analysis; expert interpretation/explanation; review of previous steps; model improvement; presentation of final model.
Deployment	Rules/regulations extraction; model implementation; final report preparation; development plan formulation; model-based decision making; utilization of results.

for subsequent analysis. This final corpus of 824,845 tweets constitutes the sole dataset used for all topic modeling and sentiment analyses reported in this study As shown in Table 2, the data filtering and preprocessing pipeline reduced the initial dataset of 6.2 million tweets to a final analytical corpus of 824,845 tweets.

We then examined yearly volume (2013–2022) to track the evolution of public interest in IoT. Mentions increased steadily from 2013–2015, dipped slightly in 2016, and rose markedly during 2017–2019. Activity peaked around 2019–2020, declined during 2020–2021—likely reflecting the COVID-19 attention shift—and then rebounded as conditions eased, with notable growth into 2022.

Topic Modeling with LDA

Topic modeling is a core text-mining technique for uncovering latent structure and relationships among documents. Latent Dirichlet Allocation (LDA) is a generative model that explains observed texts as mixtures of latent topics, helping account for why certain documents (or terms) exhibit similarity (Tong & Zhang, 2016).

We trained LDA models on the cleaned corpus using Gensim. Topic interpretability was evaluated by inspecting topic coherence across candidate models and selecting the optimal number of topics. Coherence—which captures the semantic relatedness and thematic clarity of a topic's top words—served as the primary diagnostic: higher coherence scores indicate greater accuracy and interpretability of the learned topics. As a result of this procedure, Figure 1

Table 2. Data Filtering and Preprocessing Pipeline

Stage	*Number of Tweets*
Initial raw collection	6,200,000
After initial filtering	2,614,320
After duplicate removal	2,408,961
After random sampling (50%)	1,204,480
After length filtering	871.142
Final analytical corpus	824,845

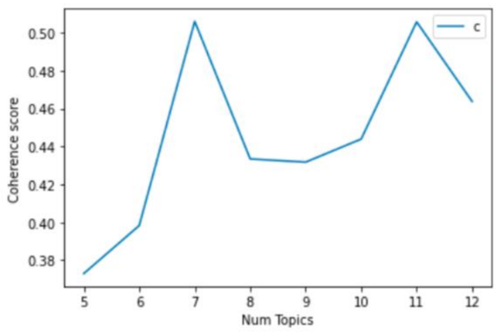

Figure. 1. Evaluation of Coherence Scores for Topics

reports the selected topic configuration and the associated coherence diagnostics.

Although coherence and perplexity provide useful indications of topic quality, we acknowledge that more comprehensive evaluation, such as human judgment or intrusion tests, was not performed due to the retrospective nature of the study.

Based on the highest coherence score at k = 7, we selected seven topics as the optimal solution. We then re-estimated the LDA model with k = 7 and assigned tweets accordingly. The keyword weights for each topic are as follow in Figure 2.

To evaluate the model's performance, we computed perplexity (lower is better) and topic coherence (higher is better). The results are summarized below in Figure 3.

Consistent with the preceding discussion, lower perplexity and higher coherence indicate better topic-modeling performance. Table 3 presents the frequently occurring keywords identified for each of the seven topics.

Each tweet was then evaluated with the fitted LDA model to determine its primary topic. The model outputs a probability distribution over topics for every tweet; the topic with the highest posterior probability was taken as the tweet's predominant topic. Using this assignment, the distribution of tweets across topics is summarized in Table 4.

Next, the topics identified through topic modeling were assigned labels based on their word distributions. Tweets with similar word distributions were grouped under the same topic. After determining the optimal number of topics as seven via LDA, the tweets word distributions were partitioned into these seven clusters. Because LDA indexes topics numerically, it is essential at this stage to assign interpretable titles to each topic. To do so, we reviewed at least 25 tweets per topic and analyzed

```
[(0,
  '0.019*"smart" + 0.014*"device" + 0.012*"amp" + 0.010*"use" + '
  '0.009*"technology" + 0.009*"new" + 0.009*"security" + 0.008*"smarthome" + '
  '0.008*"internet" + 0.008*"make" + 0.007*"connect" + 0.007*"home" + '
  '0.007*"sensor" + 0.006*"datum" + 0.006*"city"'),
 (1,
  '0.027*"gt" + 0.014*"business" + 0.013*"technology" + 0.011*"datum" + '
  '0.010*"cloud" + 0.010*"amp" + 0.009*"internet" + 0.009*"market" + '
  '0.009*"new" + 0.008*"solution" + 0.008*"industry" + 0.007*"edge" + '
  '0.007*"network" + 0.006*"digital" + 0.005*"service"'),
 (2,
  '0.062*"ai" + 0.054*"bigdata" + 0.034*"datascience" + '
  '0.025*"machinelearning" + 0.022*"python" + 0.022*"analytic" + 0.020*"iiot" '
  '+ 0.019*"deeplearne" + 0.019*"daysofcode" + 0.016*"ml" + '
  '0.014*"machinelearne" + 0.014*"javascript" + 0.013*"code" + '
  '0.012*"cybersecurity" + 0.012*"tech"'),
 (3,
  '0.027*"industry" + 0.023*"iotcommunity" + 0.023*"iiot" + 0.017*"iotpl" + '
  '0.011*"pay" + 0.010*"bigdata" + 0.010*"tech" + 0.010*"live" + 0.010*"uk" + '
  '0.009*"smartcity" + 0.008*"iotcl" + 0.008*"machine" + 0.007*"iotchannel" + '
  '0.007*"bird" + 0.007*"smartthing"'),
 (4,
  '0.031*"cybersecurity" + 0.022*"security" + 0.018*"raspberrypi" + '
  '0.017*"power" + 0.015*"maker" + 0.013*"time" + 0.013*"current" + '
  '0.013*"google" + 0.012*"infosec" + 0.012*"temperature" + 0.012*"date" + '
  '0.011*"apple" + 0.011*"weather" + 0.010*"usage" + 0.009*"memory"'),
 (5,
  '0.040*"ai" + 0.019*"rt" + 0.018*"tech" + 0.015*"cc" + 0.014*"robotic" + '
  '0.013*"mikequindazzi" + 0.012*"technology" + 0.011*"innovation" + '
  '0.009*"robot" + 0.008*"ar" + 0.008*"startup" + 0.008*"wearable" + '
  '0.007*"vr" + 0.007*"future" + 0.007*"healthtech"'),
 (6,
  '0.022*"blockchain" + 0.012*"crypto" + 0.011*"cryptocurrency" + '
  '0.011*"bitcoin" + 0.010*"tech" + 0.010*"fintech" + 0.010*"news" + '
  '0.007*"investment" + 0.007*"china" + 0.006*"startup" + 0.006*"invest" + '
  '0.005*"late" + 0.005*"btc" + 0.005*"ethereum" + 0.005*"daily"')]
```

Figure. 2. Visualization of the key word weights for the obtained topics

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Perplexity:  -8.379533636360215

Coherence Score:  0.5061044813483869
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Figure. 3. Assessment of perplexity and coherence score

their text and associated keywords to derive meaningful labels. Based on the word weights for each topic and this close reading of representative tweets, the proposed titles, revised to accurately reflect the underlying keyword distributions, are presented in Table 5.

Table 3. Frequently Occurring Key Words for the Topics

Topic	***Keywords***
1	gt, business, technology, datum, cloud, amp, internet, market, new, solution, industry, edge, network, digital, service, learn, company, read, global, use, iiot, trend, security, industrial, enterprise, today, device, help, platform, report
2	ai, bigdata, datascience, machinelearning, python, analytic, iiot, deep learning, daysofcode, ml, machine learning, javascript, code, cybersecurity, tech, cloud, rt, linux, programming, datascientist, serverless, rstat, blockchain, technology, robot, cloud computing, fintech, nlp, tensorflow, data
Topic	***Keywords***
3	Smart, device, amp, use, technology, new, security, smarthome, internet, make, connect, home, sensor, datum, city, tech, build, system, help, solution, learn, see, work, network, know, healthcare, one, app, cybersecurity, rt
4	ai, rt, tech, cc, robotic, mikequindazzi, technology, innovation, robot, ar, startup, wearable, vr, future, healthtech, industry, drone, futureofwork, automation, ronald_vanloon, digitalhealth, digital, autonomous, mt, socialmedia, mhealth, blockchain, internet, join, smartcity
5	Cybersecurity, security, raspberrypi, power, maker, time, current, google, infosec, temperature, data, apple, weather, usage, memory, pm, software, telecom, day, hack, cyber, temp, smarthome, battery, ios, privacy, attack, hpa, seo, humidity
6	Blockchain, crypto, cryptocurrency, bitcoin, tech, fintech, news, investment, china, startup, invest, late, btc, ethereum, daily, money, fund, deal, sale, india, ioe, award, buy, funding, ico, eth, stock, win, techcrunch, asia
7	Industry, iotcommunity, iiot, iotpl, pay, bigdata, tech, live, uk, smartcity, iotcl, machine, iotchannel, bird, smartthing, tehnology, essay, cam, digitalcity, webcam, Carlisle, nature, birdfeeder, birdphotography, paper, springwatch, education, amp, market, iotslam

Table 4. Number of Tweets in Different Topics

Topic Number	***Number***
0.0	188308
0.1	222575
0.2	145515
0.3	40819
0.4	61463
0.5	116304
0.6	49861

In the following sections, we discuss the results of the topic-modeling analysis after assigning titles to the topics. Figure 4 illustrates the overall temporal trends of the identified topics.

Based on Figure 4, Business & Industrial IoT has consistently been the most discussed topic over time, followed by Artificial Intelligence & Machine Learning and Smart Home. Topics such as Use of the Internet of Things, Blockchain, and Smart City exhibit slower growth in commentary, suggesting comparatively lower user engagement. Notably, despite temporal fluctuations, the overall hierarchy of public interest has remained stable. Between 2020 and 2021, all topics declined, likely reflecting the dominance of COVID-19 in public discourse; engagement with IoT-related topics rebounded markedly in 2022.

Next, we examine tweet length (measured by word count); the distribution is shown in the following chart (Figure 5).

On average, tweets contain about 200 characters. A useful way to visualize salient terms is through word clouds generated for each topic. In these analyses, the following observations were made:

- **Smart Home.** The word cloud prominently features smart, device, security, and technology, along with the token amp. The repeated emphasis on security highlights its centrality in Smart Home discourse and suggests a sustained user concern that researchers and entrepreneurs should prioritize.
- **Business Intelligence**. Frequent terms such as business, technology, and internet indicate that conversations often focus on leveraging technology within business contexts.
- **Artificial Intelligence**. Prominent terms—big data, data science, and machine learning—underscore the close relationship between IoT and AI, particularly for managing the large volumes of data generated by connected devices.
- **Smart City.** Terms like IoT community, industry, and IoT technology highlight the application of IoT in urban environments and emphasize community engagement, industry participation, and technological progress in smart-city initiatives.
- **Use of the Internet of Things**. The prominence of cybersecurity and security underscores the importance of addressing protection and privacy concerns to improve user acceptance of IoT. These issues merit prioritization to foster trust and adoption.

Table 5. Proposed Titles for Different Topics

Topic Number	*Topic Title*
1	Business / Industrial IoT / Enterprise Systems
2	Artificial Intelligence / Machine Learning
3	Smart Home
4	Emerging Technologies / Robotics / Wearables
5	IoT Usage & Security / Privacy Concerns
6	Blockchain
7	Smart City / Industrial IoT Community

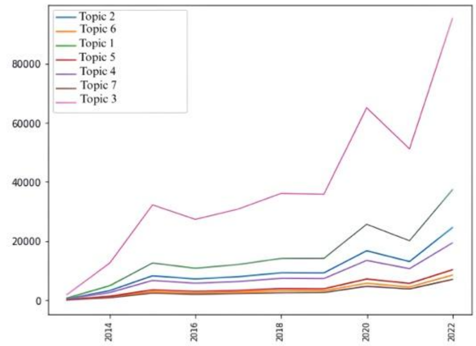

Figure. 4. Overall trend of various topics discussed in the field of Internet of Things from 2013 to 2022

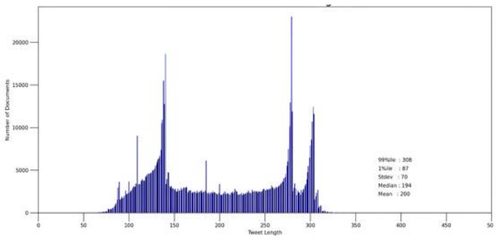

Figure. 5. Number of words in tweets

- **Emerging Technologies**. Frequent terms such as robotics, and artificial intelligence signal active discussion of cutting-edge technologies within the IoT context. For researchers, these patterns provide guidance on user-perceived opportunity areas.
- **Blockchain.** Terms including cryptocurrency, financial technology, and crypto point to a strong intersection of IoT with blockchain, particularly in digital investment and financial applications.

Note. The token amp commonly appears due to HTML decoding (i.e., “&”) rather than as Accelerated Mobile Pages. If desired, it can be mapped to & or omitted in presentation without affecting the underlying results.

Sentiment Analysis

Sentiment analysis was employed to evaluate viewpoints expressed in a dataset of IoT-related tweets from the English-language X (formerly Twitter) community. The workflow comprised three steps. First, tweet text underwent preprocessing to remove stop words, special characters, and URLs, retaining only relevant content for analysis—an essential step to refine the dataset and improve classification accuracy.

Second, the AFINN lexicon was used to classify each tweet into one of three groups: neutral, negative, or positive. While this approach was state-of-the-art at the time of data collection, we acknowledge that more recent methods, including transformer-based models, may provide improved accuracy on social media text containing emojis, hashtags, or sarcasm In order to generate a sentiment label for every tweet, this classification used natural language processing (NLP) techniques to examine lexical cues and local context within the text.

Third, we looked at the sample's sentiment distribution to describe general patterns in public perceptions of IoT. In order to shed light on public attitudes and perceptions regarding IoT technologies, we also compared sentiment patterns over time and across topics to show how perceptions differed by theme and time.

Deployment

The deployment phase is the final stage of CRISP–DM. In this study, deployment centers on interpreting the modeling outputs—particularly the predicted sentiments expressed by users regarding IoT—and translating findings into actionable insights. The results are intended to support future research and business applications, including the development of IoT solutions for commercial products. They also aim to guide researchers and inform investment decisions that enhance services and operations for active firms in this domain. These implications are discussed in the subsequent chapter.

4. Results

Based on the final corpus of 824,845 tweets, the topic-modeling results show that Business & Industrial IoT (Topic 1) is the most prominent topic, followed by Artificial Intelligence & Machine Learning (Topic 2) and Smart Home (Topic 3). The order of topics by public interest does not change over time, despite changes in the relative volumes.

As shown in Table 6, Sentiment analysis shows that 46.78% of opinions on X (formerly Twitter) about IoT are positive, 43.41% are neutral, and 9.81% are negative. All topics exhibit comparable sentiment distributions, indicating a generally favorable view of IoT technologies and associated conversations.

All of these findings provide useful information for future research, business strategy, and investment decisions in the IoT space by elucidating the prevalent themes and sentiments surrounding IoT on social media.

The sentiment analysis shows a consistent distribution of opinions across IoT-related topics, with similar shares of positive, neutral, and negative views. Across all topics, positive sentiments generally outweigh negative ones.

Table 6. Number of Positive, Negative, and Neutral Tweets Regarding Each Topic

Topic Number	*Topic Title*	*Sentiment Classification*		
		Positive Tweets	*NeutralTweets*	*NegativeTweets*
1	Business / Industrial IoT / Enterprise Systems	46.64%	43.46%	9.9%
2	Artificial Intelligence / Machine Learning	46.93%	43.36%	9.71%
3	Smart Home	46.96%	43.45%	9.59%
4	Emerging Technologies / Robotics / Wearables	46.75%	43.56%	9.69%
5	IoT Usage & Security / Privacy Concerns	46.85%	43.4%	9.75%
6	Blockchain	46.72%	43.38%	9.9%
7	Smart City / Industrial IoT Community	47.28%	42.97%	9.75%

5. Discussion and Conclusion

Our analysis of X (formerly Twitter) discourse reveals that Business & Industrial IoT dominates the IoT-related conversation on X, followed by Artificial Intelligence & Machine Learning, Smart Home, and Blockchain. While the volume of discussions fluctuates over time, the relative ranking of these themes remains stable, indicating a persistent structure in public attention. Sentiment analysis further shows broad enthusiasm for IoT—nearly half of posts are positive—and this favorable tendency is consistent across topics. Such alignment suggests a generalized optimism toward IoT diffusion rather than isolated hype cycles, reflecting widespread approval of ongoing IoT advancements.

Positioning against prior work, our findings are consistent with [54] which reported predominantly positive attitudes toward IoT using 2009–2013 Twitter data. Our larger and more recent corpus corroborates this trend while underscoring the growing salience of Smart Home discussions. Similarly, another study demonstrated the strength of supervised models for analyzing sentiment in wearables and VR, whereas our unsupervised approach captures topic-linked sentiment without labeled data—sacrificing some accuracy for scalability and domain generality. [55] applied machine- and deep-learning models to study 5G opinions; in contrast, we use unsupervised estimation to map sentiment across multiple IoT domains at scale.

The implications are twofold. For researchers, the observed stability in topic hierarchy invites longitudinal modeling of attention shifts and potential cross-topic spillovers. For practitioners, policymakers, and investors, the sustained positivity indicates favorable conditions for adoption—particularly in Smart Home—though monitoring short-term declines in sentiment may help guide risk communication and product roadmaps.

However, several limitations apply. Platform and sampling bias persist, as X users are not fully representative of the general population. The analysis covers only English-language content, leaving out perspectives from other regions and languages. Compared with task-specific supervised models, unsupervised sentiment estimation may under-detect nuances such as irony or sarcasm. These limitations suggest the value of complementary approaches, including multilingual analyses, surveys, and hybrid modeling frameworks.

Overall, this study analyzes 824,845 English-language tweets collected over a ten-year period (2013–2022) to map IoT themes and associated sentiment using LDA topic modeling and unsupervised sentiment estimation. We find that Business & Industrial IoT consistently leads public discourse, followed by Artificial Intelligence & Machine Learning and Smart Home; sentiment is predominantly positive with stable cross-topic patterns; and the hierarchy of attention remains broadly steady over time—collectively indicating broad societal acceptance of IoT developments. We recognize that the sentiment analysis method (AFINN) used in this study has limitations. Future work could apply transformer-based models or social media-specific lexicons for improved sentiment detection. A limitation of this study is that LDA topic evaluation relied only on coherence and perplexity. Human judgment and intrusion-based validation were not feasible for this historical dataset. Future studies should include these methods for a more robust evaluation.

Contributions and Future Directions

This research provides a large-scale, longitudinal view of IoT discourse and introduces a topic-linked sentiment framework connecting what people discuss to how they feel. It aligns with but extends prior Twitter-based studies through its scale and temporal scope. Future research should enhance external validity by incorporating event detection to measure sentiment shocks, expanding the analysis to multilingual and regional contexts, and integrating unsupervised pipelines with weakly or semi-supervised techniques. Triangulating these insights with survey or panel data will further enrich understanding of IoT's evolving social narrative. Our findings provide general insights, but further studies using modern sentiment analysis techniques are recommended.

Declarations

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Data Availability

All datasets used in this study are publicly available, not owned by the authors, and were utilized exclusively for research purposes.

Ethics Approval

This study did not involve human or animal subjects; therefore, institutional review board approval was not required.

Conflict of interest

The authors declare that no conflicts of interest exist.

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