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Knowledge Discovery Based on Sentiment Analysis of Public Perceptions About Generative AI on X

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Abstract:

Public discourse surrounding Generative Artificial Intelligence (GenAI) reflects diverse attitudes ranging from optimism to ethical concern, particularly as these technologies become increasingly discussed in educational contexts. This study examines public perceptions of GenAI on the social media platform X using a knowledge discovery approach that integrates multiple topic modeling techniques and Aspect-Based Sentiment Analysis (ABSA). A total of 111,675 English-language tweets collected between June 23, 2024, and June 23, 2025, were analyzed using five topic modeling methods BERTopic, Top2Vec, LDA, LSA, and NMF to identify dominant discussion themes and evaluate topic coherence. Sentiment toward specific GenAI aspects was subsequently examined using ABSA to capture fine-grained public attitudes. The results indicate that topics related to ethics and creativity are predominantly associated with negative sentiment, while innovation and cloud-related discussions show higher levels of positive sentiment. Education-related topics are largely characterized by neutral sentiment, suggesting exploratory and informational discourse. These findings highlight the importance of addressing ethical awareness, trust, and AI literacy in informatics education. By combining multi-model topic analysis with aspect-level sentiment interpretation, this study provides methodological insights and empirical evidence to support responsible GenAI integration in educational contexts.

Keywords: *Aspect-Based Sentiment Analysis, Generative Artificial Intelligence, Knowledge Discovery, Social Media X, Topic Modeling*

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Introduction

Artificial Intelligence (AI) has advanced rapidly in recent years, particularly with the emergence of Generative AI (GenAI), which is capable of producing new content in various forms, including text, images, audio, and even video, with a high degree of realism. This technology is built using deep learning approaches, including Generative Adversarial Networks (GANs), Variational Autoencoders (VAEs), Transformers, Diffusion Models, and other probabilistic methods (Desai & Riedl, 2024; Sengar et al., 2024). This rapid development is evident in the emergence of various popular models, such as ChatGPT, DALL-E, and Midjourney, which facilitate the automatic production of creative content (Islam & Greenwood, 2024).

In addition to offering significant benefits for content production efficiency and creativity, GenAI also raises serious concerns regarding ethics, privacy, and intellectual property rights (Miyazaki et al., 2023; Nurlanuly, 2025). One of the primary concerns is the potential misuse of deepfake technology for information manipulation, which can harm reputations and erode public trust in information (Geiger, 2024). On the other hand, the practice of using copyrighted works to train AI models raises complex legal challenges (Desai & Riedl, 2024; Geiger, 2024).

Studies mapping public perceptions of GenAI on social media reveal sentiments ranging from optimism to anxiety (Arowosegbe et al., 2024; Miyazaki et al., 2023). Machine learning-based sentiment analysis has been highlighted as an effective tool for revealing broad concerns, particularly regarding ethics and privacy (Nurlanuly, 2025; Utami, 2022). However, existing studies largely focus on overall sentiment polarity or thematic frequency, providing limited insight into how specific aspects of GenAI are evaluated emotionally by the public.

Sentiment analysis, as part of Natural Language Processing (NLP), plays a crucial role in identifying and categorizing users' emotional attitudes in text, typically into positive, negative, or neutral categories (Pratiwi & Tania, 2025; Sujana, 2024). When applied to large-scale, unstructured social media data, sentiment analysis facilitates a deeper understanding of societal attitudes toward emerging technologies. More advanced approaches, such as Aspect-Based Sentiment Analysis (ABSA), extend this capability by associating sentiment expressions with specific aspects or dimensions of a topic, thereby producing more fine-grained and actionable insights.

X (formerly Twitter), a microblogging platform, allows real-time information sharing via tweets and has proven effective in amplifying opinions, reflecting public interests, and mobilizing collective discourse (Agustina et al., 2021; Kristianto et al., 2021; Suhendra & Selly Pratiwi, 2024). These features make it suitable for analyzing public perception of GenAI.

Research Gap and Contribution

While prior studies, most notably Miyazaki et al. (2023), have examined public sentiment toward Generative AI on social media using large-scale Twitter data, existing research primarily focuses on occupation-based analysis and general sentiment patterns or high-level thematic clustering. Such approaches do not explicitly incorporate fine-grained aspect-level sentiment analysis that captures public attitudes toward specific dimensions of Generative AI, such as ethical concerns, educational relevance, or technological reliability. In addition, the implications of public Generative AI discourse for informatics education remain underexplored, despite the increasing adoption of GenAI tools in educational contexts.

Addressing these gaps, this study integrates multiple topic modeling techniques BERTopic, Top2Vec, LDA, LSA, and NMF with Aspect-Based Sentiment Analysis (ABSA) within a knowledge discovery framework. Unlike previous studies, this research systematically compares topic modeling paradigms and analyzes sentiment at the aspect level, while explicitly interpreting the findings through an educational lens. Consequently, this study contributes methodologically by demonstrating the value of multi-model and aspect-based analysis, and substantively by providing insights that support AI literacy development and ethical awareness in informatics education. Unlike prior studies that primarily rely on single-topic modeling approaches or general sentiment polarity, this study uniquely integrates multi-model topic modeling with aspect-based sentiment analysis, explicitly interpreting the findings within the context of informatics education.

Educational Relevance

Understanding public sentiment toward Generative AI is particularly relevant to informatics education, as students represent both active users and future developers of AI technologies. Public concerns regarding ethics, authorship, bias, and privacy are consistent with findings in higher education contexts, where students express both optimism and concern toward GenAI integration (Arowosegbe et al., 2024; Singh & Strzelecki, 2025). Insights derived from sentiment analysis can support the integration of AI literacy into informatics curricula by emphasizing not only technical competencies but also ethical reasoning and critical awareness, thereby informing curriculum design, instructional strategies, and policy discussions related to responsible AI education.

Theoretical Framework

This study is conceptually framed using established theories of technology adoption and educational technology integration to support the interpretation of public sentiment toward Generative Artificial Intelligence (GenAI), rather than to test causal relationships (Hasan Emon, 2023). The theoretical frameworks are employed as analytical lenses to contextualize sentiment patterns identified through topic modeling and Aspect-Based Sentiment Analysis (ABSA), particularly in the context of education, where the adoption of GenAI remains a subject of ongoing debate and negotiation (Arowosegbe et al., 2024).

The Technology Acceptance Model (TAM) emphasizes that perceived usefulness and perceived ease of use play a central role in shaping individuals' acceptance of new technologies (Ibrahim et al., 2025). Within the context of this study, public sentiment expressed on social media is interpreted as a collective reflection of these perceptions. Positive sentiment toward specific GenAI aspects may indicate perceived benefits and functional value, whereas negative sentiment may reflect usability concerns, ethical apprehensions, or resistance to adoption. Recent empirical research has demonstrated that TAM continues to be a relevant framework for understanding the acceptance of Generative AI in educational settings, particularly among educators and students who evaluate GenAI tools based on their pedagogical usefulness and perceived risks (Ghimire & Edwards, 2024).

In addition, the Diffusion of Innovations theory provides a complementary perspective by highlighting the role of communication channels and social discourse in shaping how innovations spread within society. From this viewpoint, social media discussions on platform X are understood as part of the diffusion process, where public narratives, endorsements, and concerns contribute to the formation and evolution of attitudes toward GenAI. Studies applying Diffusion of Innovations theory to Generative AI adoption in higher education suggest that factors such as perceived advantages, compatibility with existing practices, and complexity significantly influence adoption decisions at the institutional and individual levels (Singh & Strzelecki, 2025).

From an educational perspective, public sentiment related to the use of GenAI in learning contexts, ethical considerations, and trust in AI systems can be interpreted in relation to AI literacy and pedagogical readiness within informatics education. Empirical evidence from higher education contexts indicates that while Generative AI is often perceived as beneficial for learning efficiency and academic productivity, concerns regarding academic integrity, ethical use, and the lack of clear institutional guidelines remain prominent (Arowosegbe et al., 2024). These concerns underscore the importance of preparing students not only to use GenAI tools effectively but also to engage critically and responsibly with AI technologies as part of informatics education.

Together, these theoretical perspectives inform the formulation of the research questions and guide the interpretation of findings by linking public sentiment patterns to technology acceptance, innovation diffusion, and educational readiness. Rather than serving as predictive models, the theories provide a conceptual foundation for discussing how public perceptions of Generative AI can inform the development of AI literacy, ethical awareness, and curriculum design within informatics education.

Research Questions

Based on the identified research gap and theoretical framing, this study is guided by the following research questions.

RQ1. What dominant topics emerge from public discussions on Generative AI on the social media platform X?

RQ2. How are sentiments distributed across different aspects of Generative AI, such as ethics, creativity, education, and technological reliability?

RQ3. How can public sentiment patterns toward Generative AI inform ethical awareness and AI literacy in informatics education?

These research questions structure the analytical process and serve as a reference point for interpreting the results and discussion sections.

Research Method

This research employs a computational approach to analyze unstructured textual data, similar to the one used in previous studies involving topic modeling techniques (Pratiwi & Tania, 2025). The research workflow conducted in this study is illustrated in Figure 1.

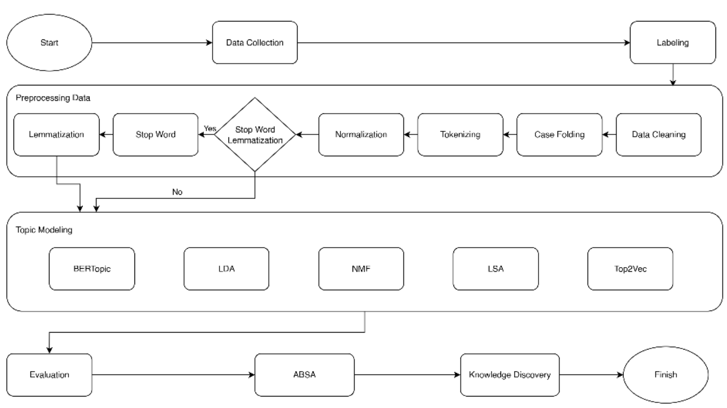

Figure 1. Research workflow for generative AI sentiment analysis

Figure 1 illustrates the overall research workflow, beginning with data collection from platform X, followed by text preprocessing, topic modeling, topic quality evaluation, and Aspect-Based Sentiment Analysis. The final stage integrates these outputs within a knowledge discovery framework to generate interpretable insights into public perceptions of Generative AI.

Data Collection

Data were collected from the social media platform X using a daily crawling method with the help of the tweet-harvest tool, which was executed through npx. The collection was carried out based on the keyword "generative AI lang:en," restricted to the English language, within the time frame of June 23, 2024, to June 23, 2025. The data retrieval process was conducted daily with a maximum limit of 300 tweets per day, and the results were stored in CSV format. Although this limit may introduce potential sampling bias, it was consistently applied each day to keep the amount of collected data balanced over time. In addition, collecting data continuously for an entire year helped reduce representational issues and capture long-term variations in public discussions. All collected data consisted of publicly accessible tweets and did not involve private user information, ensuring that the data collection process complied with ethical standards for social media research.

Preprocessing

Preprocessing was conducted through several stages, beginning with data cleaning to remove duplicate tweets and address missing values. All text was then converted to lowercase through case folding to ensure uniformity. Special characters including emojis, mentions, URLs, hashtags, numbers, and other non-alphabetic symbols were removed. The cleaned text was tokenised and expanded into individual rows using the explode technique. Non-standard words and typographical variations were corrected using a normalization dictionary to produce standardized text. Although this study does not incorporate a dedicated mechanism for handling deeper linguistic subtleties, the preprocessing steps employed are sufficient to reduce surface-level noise and retain the essential contextual structure required for reliable downstream analysis.

Topic Modeling

This study employed five major approaches with strong theoretical foundations: Latent Dirichlet Allocation (LDA), Latent Semantic Analysis (LSA), Non-negative Matrix Factorization (NMF), BERTopic, and Top2Vec. LDA models documents as a probabilistic distribution of topics (Pratiwi & Tania, 2025).

In this study, the LDA model was trained using a fixed twelve topic configuration obtained through iterative tuning to balance topic interpretability and coherence in short text social media data. Symmetric prior assumptions were applied to both document topic and topic word distributions to reduce bias toward dominant topics and to ensure stable topic formation across the corpus.

LSA applies singular value decomposition to project high dimensional term document matrices into a lower dimensional semantic space (Agustina et al., 2021). The dimensionality of the reduced semantic space was aligned with the twelve-topic configuration to ensure methodological comparability across models while suppressing noise commonly found in informal and short social media texts.

NMF factorizes the term document matrix into two non-negative matrices representing topic word and document topic associations (Agustina et al., 2021). A twelve-topic structure was employed with non-negativity constraints to ensure additive and interpretable topic representations and to minimize semantic overlap among topics. Embedding based approaches were employed to better capture contextual semantics in short texts.

BERTopic utilized transformer-based document embeddings generated by the all MiniLM L6 v2 model, producing 384 dimensional semantic vectors. These embeddings were reduced using UMAP configured to preserve local semantic neighborhoods through fifteen nearest neighbors and cosine distance. Topic clustering was then performed using HDBSCAN with a minimum cluster size of 1060 documents to retain only semantically dense topic groups. Topic representations were generated using CountVectorizer with unigram and bigram ranges while excluding English stopwords, enabling the extraction of representative keywords for each topic (Grootendorst, 2022).

Top2Vec employed the same embedding architecture to ensure methodological consistency, mapping documents and words into a shared semantic vector space. Dimensionality reduction and density-based clustering were conducted using UMAP and HDBSCAN with a minimum cluster size of 1050 documents to identify coherent topic regions emerging naturally from dense semantic structures without predefined topic assumptions (Egger & Yu, 2022; Karas et al., 2022; Krishnan, 2023).

To ensure methodological consistency across all models, the number of topics was determined through an iterative tuning process in which multiple candidate configurations were evaluated using coherence metrics and qualitative interpretability. The final configuration employed a fixed twelve topic setting to prevent topic merging or overfragmentation in short text social media corpora. All models were trained using the same preprocessing pipeline and evaluated using identical coherence metrics, namely C_V, UMass, UCI, and NPMI, ensuring a fair and systematic comparative assessment.

Evaluation

Topic quality evaluation was conducted using four coherence metrics, namely C_V, UMass, UCI, and NPMI. The C_V metric assesses semantic relatedness among words based on their co-occurrence patterns and cosine similarity, where higher values indicate more coherent topics (Rahimi et al., 2023). UMass measures topic coherence through the log probability of word co-occurrences within the internal corpus, with optimal quality indicated by values closer to 0 (Rahimi et al., 2023). The UCI metric is based on Pointwise Mutual Information calculated from word pair co-occurrences and produces positive scores for topics with stronger internal consistency, while NPMI normalizes PMI values within a range from -1 to 1, where values approaching 1 indicate high topic coherence (Rahimi et al., 2023). Although these metrics are effective for assessing topic consistency, several studies emphasize that automated coherence scores do not always align perfectly with human judgment, and therefore require contextual interpretation in the analytical discussion (Doogan & Buntine, 2021; Rüdiger et al., 2022).

Aspect-Based Sentiment Analysis (ABSA)

ABSA generally combines topic modeling techniques with transformer-based models to achieve high accuracy in classifying aspects and sentiments within text (Agustina et al., 2021; Pranatawijaya et al., 2024). In this study, ABSA was employed to identify and classify sentiments toward specific dimensions of Generative AI, including copyright issues, social impacts, and technological reliability, thereby producing more comprehensive analytical results.

Sentiment labeling was performed using the transformer-based model cardiffnlp/twitter-roberta-base-sentiment. This model was selected because it is pre-trained on large-scale Twitter data and has demonstrated strong performance in capturing sentiment patterns in short and informal social media texts. Model reliability was evaluated using 1,186 manually annotated tweets, representing 5% of the dataset, selected through stratified sampling to ensure balanced sentiment classes (Zharif Mustaqim et al., 2024).

The aspects analyzed in this study were defined based on thematic categories derived from topic modeling outputs and subsequently validated through manual examination to ensure conceptual coherence. These defined aspects then served as the basis for sentiment classification, enabling ABSA to capture more fine-grained and representative public perceptions of each Generative AI dimension.

Knowledge Discovery

This process aims to identify meaningful patterns and hidden relationships in unstructured data, including social media data, to generate deeper insights that support decision making (Ariannor et al., 2024). This approach can leverage a combination of analytical techniques, such as topic modeling, sentiment analysis, and embedding-based text representations, to enhance accuracy and depth of understanding of the data (Novalia et al., 2024; Pratiwi & Tania, 2025). In this study, knowledge discovery was implemented by integrating the results from the five topic modeling methods (LDA, LSA, NMF, BERTopic, and Top2Vec), Aspect-Based Sentiment Analysis (ABSA), and general sentiment classification to comprehensively map public perceptions of Generative AI both thematically and emotionally. By integrating thematic structures and aspect-level sentiment, this knowledge discovery process supports informed decision making, particularly in understanding societal concerns and educational implications related to Generative AI adoption.

Result and Discussion

Result

Data Collection

This study collected a total of 111,675 tweets from the social media platform X (Twitter) using the keyword "generative ai" over one year. Each tweet contained text content (full_text), publication time (created_at), and interaction metrics, including retweets, replies, likes, and quotes. Data were retrieved daily with a maximum limit of 300 tweets per day, resulting in a large corpus while ensuring consistent temporal coverage. Although the dataset is large, the daily limit of 300 tweets may introduce sampling bias by missing peak conversation periods. This risk was mitigated by collecting data at consistent daily intervals and focusing the analysis on long-term trends rather than short-lived spikes.

Labeling

Labeling was carried out using the Transformer model cardiffnlp/twitter-roberta-base-sentiment, implemented through the Transformers library and PyTorch. This model classified each normalized text into three sentiment categories: positive, neutral, and negative. Table 1 presents representative examples of automatic labeling, illustrating positive appreciation, neutral analytical discussion, and negative dissatisfaction toward generative AI.

Table 1. Sentiment labeling results

Label	Text
Positive	an important and very informative zoom call happening now discussing navigating generative ai with the archival producers alliance tool kit thank you so much to
Neutral	generative ai in writing raises important questions about originality and copyright is it fair to compare ai training to using copyrighted works in textbooks without permission let rethink how we view automatic identification system role in creativity and authorship
Negative	why is every ad on television about generative ai genuinely every single one most being endorsed by big time actors incredibly awful

Model reliability was evaluated using 1,186 manually annotated tweets, representing 5% of the data from each sentiment class, selected through stratified sampling to ensure balanced class representation (Zharif Mustaqim et al., 2024). The evaluation yielded an overall accuracy of 0.7951, with a macro-average F1-score of 0.79 and a weighted F1-score of 0.80, indicating robust and balanced performance across classes. The model demonstrated strong performance in identifying positive and negative sentiments, while neutral sentiment showed lower recall, reflecting ambiguity in emotionally implicit texts.

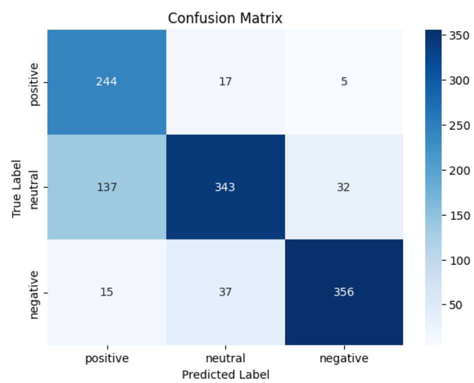

Figure 2. Confusion matrix of sentiment classification result

Figure 2 shows that most misclassifications occur between neutral and polarized classes, particularly when neutral texts are predicted as positive or negative. This result indicates that neutral sentiment remains the most challenging category to classify accurately in social media text.

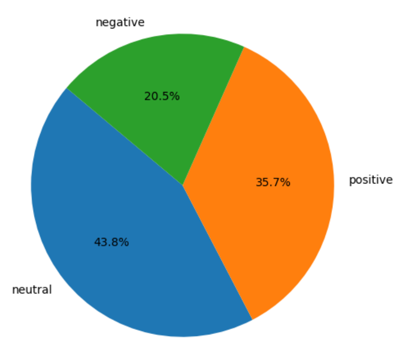

Figure 3. Sentiment distribution across generative AI topics

Figure 3 shows that neutral sentiment dominates the dataset, accounting for 43.8%, followed by positive sentiment at 35.7%, and negative sentiment at 20.5%. This corresponds to 48,146 neutral tweets, 39,291 positive tweets, and 22,610 negative tweets, respectively.

To highlight the characteristic words in each sentiment category, WordCloud visualizations were used based on classification results. Each WordCloud displays the most frequently occurring words in the corresponding group.

Figure 4. WordCloud of positive sentiment

Figure 5. WordCloud of neutral sentiment

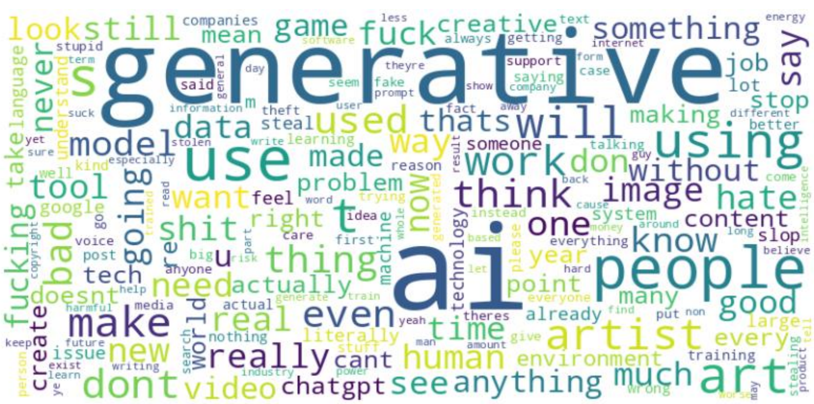

Figure 6. WordCloud of negative sentiment

Figure 4 shows a positive sentiment dominated by words such as "future," "innovation," "help," and "create." Figure 5 reflects neutral sentiment through terms such as data, language, model, and system. Figure 6 presents negative sentiment, prominently featuring words such as "problem," "hate," and "fake," along with informal or harsh expressions. These illustrations reinforce the semantic differences across sentiment classes and support the sentiment labeling outcomes.

Preprocessing

The preprocessing stage consisted of three main steps, including data cleaning, case folding, and normalization. Data cleaning was conducted to ensure consistency by deleting 2,276 duplicate items in the full_text column and eliminating non-linguistic elements, including emojis, URLs, mentions, hashtags, retweets, numbers, and other symbols, utilizing Python routines. This yielded 110,047 valid tweets for examination. Case folding was then implemented to transform all characters to lowercase, eliminating discrepancies due to capitalization. Finally, normalization was performed using a normalization dictionary to standardize non-standard words, spelling variations, and typographical errors into their correct forms. Table 2 illustrates examples of these three steps.

Table 2. Preprocessing results

No.	Operation	Description
1	Cleaning Text	I'm saying it in a tweet too. To say VOCALOID:AI isn't generative or poses no ethical problems only makes you look ignorant to the people with actual concerns about the technology and shows you have not done enough research into understanding AI and AI Voices.
2	Case Folding	I'm saying it in a tweet too to say vocaloidai isnt generative or poses no ethical problems only makes you look ignorant to the people with actual concerns about the technology and shows you have not done enough research into understanding ai and ai voices
3	Normalization	I am saying it in a tweet too to say vocaloid ai is not generative or poses no ethical problems only makes you look ignorant to the people with actual concerns about the technology and shows you have not done enough research into understanding ai and ai voices

Topic Modeling

BERTopic

BERTopic identified twelve dominant topics reflecting key areas of Generative AI discourse, including art, business and innovation, healthcare, security, chatbots, cloud services, language models, consumer devices, search technologies, and ethical legal issues. The detailed results of BERTopic are presented in Table 3.

Table 3. BERTopic results

ID	Count	Label	Name	Representation
0	39711	art	0_ai_generative_generative ai_art	['ai', 'generative', 'generative ai', 'art', 'like', 'just', 'use', 'people', 'using', 'artists']
1	15629	business	1_ai_generative ai_generative_business	['ai', 'generative ai', 'generative', 'business', 'marketing', 'education', 'tech', 'innovation', 'future', 'customer']
2	3192	healthcare	2_healthcare_ai_health_generative	['healthcare', 'ai', 'health', 'generative', 'generative ai', 'medical', 'ai healthcare', 'drug', 'patient', 'care']
3	2738	security	3_security_cybersecurity_ai_generative ai	['security', 'cybersecurity', 'ai', 'generative ai', 'generative', 'data', 'privacy', 'cyber', 'risks', 'ai cybersecurity']
4	2316	digital_asset	4_non fungible_fungible_non_token	['non fungible', 'fungible', 'non', 'token', 'tokens', 'fungible token', 'ai', 'decentralized', 'blockchain', 'paris']
5	1950	chatbot	5_chatgpt_ai_generative_generative ai	['chatgpt', 'ai', 'generative', 'generative ai', 'chat', 'chatbots', 'like', 'chatbot', 'like chatgpt', 'chatgpt generative']
6	1892	cloud	6_amazon_amazon web_web services_services	['amazon', 'amazon web', 'web services', 'services', 'web', 'ai', 'generative ai', 'generative', 'bedrock', 'amazon bedrock']
7	1763	graphic	7_nvidia_ai_graphics_graphics processing	['nvidia', 'ai', 'graphics', 'graphics processing', 'processing', 'generative', 'generative ai', 'processing unit', 'unit', 'nim']
8	1543	language	8_language_language model_large language_large	['language', 'language model', 'large language', 'large', 'model', 'ai', 'generative', 'ai large', 'generative ai', 'model generative']
9	1271	device	9_apple_iphone_apple intelligence_ai	['apple', 'iphone', 'apple intelligence', 'ai', 'generative', 'generative ai', 'intelligence', 'siri', 'features', 'galaxy']
10	1202	search	10_search_engine_engine optimization_search engine	['search', 'engine', 'engine optimization', 'search engine', 'optimization', 'google', 'ai search', 'ai', 'generative', 'generative ai']
11	1078	ethics	11_legal_law_ai_ai legal	['legal', 'law', 'ai', 'ai legal', 'generative ai', 'generative', 'legal tech', 'lawyers', 'tech', 'firms']

Top2Vec

Top2Vec extracted twelve high-level topics that emphasize art and creativity, innovation, education, security, chatbots, digital assets, cloud ecosystems, language technologies, healthcare, hardware, gadgets, and ethics. A summary of the identified topics is shown in Table 4.

Table 4. Top2Vec results

topic_num	topic_size	top_words	label
0	44375	ai, generative, gans, artificial, creativity, gan, procedural, neural, multimodal, creations, intellectual	art
1	22853	ai, generative, innovators, innovate, innovation, technological, gans, industrial, enterprise, automation	innovation
2	7576	ai, generative, learns, intellectual, educational, learners, learning, ideation, gans, education	education
3	5262	ai, cybersecurity, generative, adversarial, security, hackers, cyberattacks, automation, programmed, hacking	security
4	5226	chatbots, chatbot, ai, chatgpt, generative, chat, programmed, chats, conversational, conversations	chatbot
5	4797	ai, crypto, generative, creators, artificial, creations, tokens, creator, tokenized, agents	digital_asset
6	4454	ai, amazons, automation, amazon, alexa, agents, ecommerce, cloud, generative, agent	cloud
7	4426	generative, ai, chatbots, learns, languages, language, neural, gans, programmed, ideation	language
8	3644	ai, generative, artificial, medicine, biotech, neural, automated, gans, medical, healthcare	healthcare
9	2658	ai, nvidia, nvidias, generative, tensorflow, deepmind, intel, openai, gans, gan	hardware
10	2399	ai, ios, apple, generative, apps, iphone, deepmind, ipad, iphones, artificial	gadgets
11	2377	ai, attorneys, lawyers, litigation, lawyer, law, generative, lawsuits, intellectual, patents	ethics

NMF

The NMF model generated twelve interpretable topics, encompassing leadership, service, future orientation, data and analytics, ethics, learning, art, public opinion, models, technology, applications, and innovation. The NMF topic distribution is presented in Table 5.

Table 5. NMF results

TopicID	Keywords	label
0	more, ai, generative, read, chief, officer, technology, tech, here, innovation"	leadership
1	service, new, web, amazon, generative, ai, business, innovation, customer, technology	service
2	ai, generative, tech, innovation, future, power, news, agent, human, strategy	future
3	datum, science, generative, data, analytic, analysis, machine, insight, drive, privacy	data
4	work, generative, artist, just, future, human, other, steal, take, say	ethics
5	learn, ai, machine, tool, generative, learning, code, course, software, deep	learning
6	art, create, generative, artist, ai, token, tool, fungible, non, image	art
7	make, people, just, generative, so, think, ai, get, thing, go	opinion
8	model, language, large, generative, processing, natural, new, prompt, train, generation	model
9	generative, technology, intelligence, world, search, system, company, artificial, content, explore	technology
10	use, generative, ai, tool, case, create, image, say, chatgpt, generate	application
11	ai, tech, innovation. business, future, news, agent, power, strategy, trend	innovation

LDA

LDA identified twelve probabilistic topics related to industry, tools, models, science, digital assets, media, user experience, usage, art, cloud services, education, and innovation. The full LDA results are summarized in Table 6.

Table 6. LDA results

TopicID	Keywords	Label
0	ai, generative, company, year, tech, news, new, market, technology, state	industry
1	content, adobe, creation, ai, graphic, feature, generative, processing, unit, photoshop	tools
2	ai, model, generative, language, learning, large, machine, intelligence, artificial, prompt	model
3	data, ai, generative, science, agent, privacy, chain, linkedin, quality, property	science
4	game, non, token, generative, ai, fungible, world, gaming, player, blockchain	digital_asset
5	ai, generative, video, art, image, create, text, tool, content, new	media
6	user, ai, generative, design, experience, app, interface, feature, personal, computer	uiux
7	ai, generative, use, like, know, get, make, want, need, question	usage
8	ai, generative, people, like, use, work, using, used, art, artist	art
9	ai, generative, service, google, amazon, web, cloud, search, system, engine	cloud
10	ai, generative, course, project, use, new, tool, education, join, free	education
11	ai, generative, business, innovation, future, technology, tech, industry, chief, officer	innovation

LSA

LSA extracted twelve broad semantic themes, including models, services, cloud infrastructure, art, science, digital assets, applications, security, media, productivity, search, and education. The LSA topic summary is shown in Table 7.

Table 7. LSA rresults

TopicID	Keywords	label
1	model, language, use, data, like, large, learning, art, new, just	model
2	model, language, large, learning, data, machine, amazon, services, processing, natural	service
3	amazon, services, web, data, business, innovation, tech, future, new, cloud	cloud
4	amazon, services, web, art, model, large, language, bedrock, people, using	art
5	learning, machine, data, art, science, deep, people, analytics, just, scientist	science
6	art, future, digital, fungible, innovation, non, creativity, tech, new, token	digital_asset
7	use, art, data, cases, business, learn, chief, toes, language, dip	application
8	data, using, just, science, analytics, privacy, security, cloud, like, model	security
9	content, tools, new, features, adobe, data, photoshop, google, express, premium	media
10	using, tools, google, intelligence, artificial, stop, chatgpt, prompt, engineering, productivity	productivity
11	like, google, search, marketing, tools, intelligence, engine, artificial, chatgpt, optimization	search
12	intelligence, artificial, tools, like, general, apple, used, data, engineering, training	education

Evaluation

BERTopic

A total of 12 main topics were successfully identified and assessed to determine the strength of word associations within each topic. The evaluation results are presented in Table 8.

Table 8. BERTopic coherence scores

TopicID	UMass	C_V	UCI	NPMI
0	-2.4819	0.5051	0.1172	0.0304
1	-3.2300	0.4691	-0.1118	0.0437
2	-3.0395	0.7121	1.5102	0.1792
3	-2.8167	0.6354	1.0432	0.1392
4	-2.0042	0.8270	2.1894	0.2810
5	-3.2811	0.5248	0.4876	0.0795
6	-1.3922	0.7019	1.5409	0.2764
7	-2.7855	0.6661	0.5427	0.1687
8	-0.0741	0.6779	1.0329	0.2759
9	-3.8003	0.6050	0.8477	0.1397
10	-0.5965	0.6684	1.3099	0.2185
11	-2.6186	0.6486	1.1349	0.1431

The evaluation results show that topics with ID 4 and 6 consistently have the highest quality across all metrics, with C_V coherence scores of 0.8270 and 0.7019, and UCI scores of 2.1894 and 1.5409. This indicates that the words within these topics frequently co-occur and have strong semantic relationships. Conversely, topic 1 shows the lowest coherence, with C_V at 0.4691 and UCI at -0.1118, suggesting a lack of contextual uniformity among its words.

Top2Vec

Table 9. Top2Vec coherence scores

TopicID	C_V	UMass	UCI	NPMI
0	0.2841101461	-10.15909006	-5.085612106	-0.1649119095
1	0.3412906063	-8.399655898	-4.714780092	-0.1531763913
2	0.3978210693	-12.50420564	-6.022656163	-0.194836426
3	0.3572912433	-11.32745146	-5.831150989	-0.175948079
4	0.3266477082	-10.52283924	-5.442999724	-0.1765700719
5	0.3261002366	-7.729120255	-3.359664744	-0.1048738814
6	0.2600421575	-8.218194323	-3.737970547	-0.1188086505
7	0.3232846224	-10.57012492	-5.479485344	-0.179170805
8	0.3223632938	-10.33791973	-6.15914753	-0.2111406233
9	0.3961060229	-11.13355704	-6.316082715	-0.2184000681
10	0.3438762001	-11.09812945	-5.756333827	-0.1840090289
11	0.3293856892	-11.36512004	-5.868910087	-0.1826313573

Table 9 presents the results of the coherence evaluation for the Top2Vec model. Based on Table 9, the topic with the highest C_V score is topic 2 (Education) with a value of 0.3978, while the lowest C_V score is found in topic 6 (Cloud) at 0.2600. For the UMass metric, the highest value is held by topic 5 (Digital Asset) at -7.7291, while the lowest is in topic 2 (Education) at -12.5042. In the UCI metric, topic 5 (Digital Asset) again obtained the highest score at -3.3597, and topic 9 (Hardware) had the lowest at -6.3161. Meanwhile, the highest NPMI score was recorded in topic 5 (Digital Asset) at -0.1049, and the lowest in topic 9 (Hardware) at -0.2184. These results indicate differences in quality and keyword association across topics in the Top2Vec model.

NMF

Table 10 presents the coherence evaluation results of the NMF model.

Table 10. NMF coherence scores

TopicID	C_V	UMass	UCI	NPMI
0	0.4337964733	-2.965068752	0.07827549819	0.02145142364
1	0.5397076468	-2.759308017	0.3421211109	0.05440703572
2	0.4024078936	-3.668303373	0.01285828869	0.0100348422
3	0.5307821057	-3.465856973	0.2146139415	0.04543841409
4	0.463103344	-3.203450525	0.1968491986	0.02821237303
5	0.5163573968	-3.083712019	0.2489591708	0.03993234895
6	0.4632770192	-3.052550577	0.1899294882	0.03792359507
7	0.5438516111	-2.711931966	0.4206613453	0.06099282207
8	0.5425677241	-3.177208301	0.2101832355	0.04294749455
9	0.3578825606	-3.20400718	-0.02488064839	0.002814529738
10	0.3954580856	-3.196960174	0.07188719455	0.01613146574
11	0.3839623973	-3.568514791	-0.06365725103	0.0002434788851

Based on Table 10, topic 7 (Opinion) had the highest coherence scores across C_V (0.5439), UMass (-2.7119), UCI (0.4207), and NPMI (0.0610), which indicates good interpretability. Conversely, the lowest coherence was found in topic 9 (Technology) for C_V (0.3579), topic 2 (Future) for UMass (-3.6683), and topic 11 (Innovation) for UCI (-0.0637) and NPMI (0.0002), indicating relatively low interpretability for these topics.

LDA

Table 11 presents the coherence evaluation results of the LDA model.

Table 11. LDA coherence scores

TopicID	C_V	UMass	UCI	NPMI
0	0.4292016492	-3.711118367	0.1233781506	0.01977421193
1	0.4187166429	-4.577584924	-0.557997689	0.02239016234
2	0.5624133818	-3.238891546	0.2756705234	0.05380285479
3	0.2827311353	-6.499782284	-2.216322043	-0.03628265482
4	0.5615299231	-4.175627743	0.05071245467	0.07211715647
5	0.4876773506	-3.090648773	0.291208322	0.04364327829
6	0.4090639751	-4.507804599	-0.4402600415	0.0105089898
7	0.4431432448	-3.172187137	0.2376151106	0.0347780956
8	0.526558741	-2.882453641	0.3240922278	0.04765522828
9	0.4375703392	-3.84713479	-0.1936072315	0.03121732211
10	0.4258530312	-3.438841759	0.1389797951	0.02441163847
11	0.5415856068	-3.014431754	0.3172986205	0.04811561162

Based on Table 11, topic 2 (Model) had the highest C_V coherence score (0.5624), while topic 3 (Science) had the lowest (0.2827). The highest UMass coherence was for topic 8 (Art) at -2.8825, while the lowest was for topic 3 (Science) at -6.4998. For UCI, topic 5 (Media) showed the highest score (0.2912), while topic 3 (Science) had the lowest (-2.2163). The highest NPMI score was in topic 4 (Digital Asset) at 0.0721, while the lowest was in topic 3 (Science) at -0.0363

LSA

Table 12 presents the coherence evaluation results of the LSA model. Based on Table 12, the topic with the highest C_V score was topic 2 (Service), at 0.7222, while the lowest C_V score was for topic 7 (Application), at 0.2199. For the UMass metric, the best score was achieved by topic 3 (Cloud) at -2.4374, and the worst was for topic 7 (Application) at -7.3644. On the UCI metric, topic 9 (Media) had the highest coherence (1.1277), while topic 7 (Application) again ranked lowest (-3.4618). In the NPMI metric, topic 2 (Service) achieved the highest score (0.1868), while topic 7

(Application) recorded the lowest (-0.1064). This evaluation indicates that topics such as Service, Cloud, and Media exhibited good topic quality, whereas the Application topic was relatively less coherent.

Table 12. LSA coherence scores

TopicID	C_V	UMass	UCI	NPMI
0	0.2841101461	-10.15909006	-5.085612106	-0.1649119095
1	0.3412906063	-8.399655898	-4.714780092	-0.1531763913
2	0.3978210693	-12.50420564	-6.022656163	-0.194836426
3	0.3572912433	-11.32745146	-5.831150989	-0.175948079
4	0.3266477082	-10.52283924	-5.442999724	-0.1765700719
5	0.3261002366	-7.729120255	-3.359664744	-0.1048738814
6	0.2600421575	-8.218194323	-3.737970547	-0.1188086505
7	0.3232846224	-10.57012492	-5.479485344	-0.179170805
8	0.3223632938	-10.33791973	-6.15914753	-0.2111406233
9	0.3961060229	-11.13355704	-6.316082715	-0.2184000681
10	0.3438762001	-11.09812945	-5.756333827	-0.1840090289
11	0.3293856892	-11.36512004	-5.868910087	-0.1826313573

Aspect-Based Sentiment Analysis (ABSA)

Aspect-based sentiment analysis was conducted to examine public sentiment toward specific topics identified through the five topic modeling approaches. A total of 11 main topics were determined by consolidating topic labels generated by BERTopic, Top2Vec, LDA, LSA, and NMF, based on their highest coherence scores and most frequent occurrences. Each tweet that had been assigned a sentiment label was subsequently mapped to one of these topics. Figure 7 presents the distribution of sentiment across topics using a bar chart visualization.

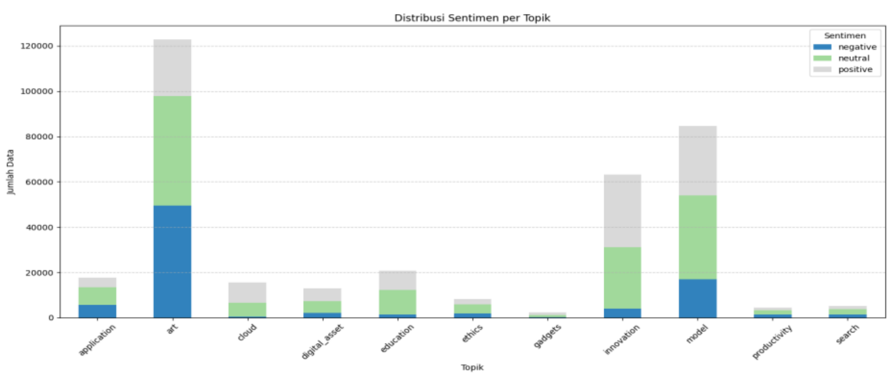

Figure 7. ABSA sentiment distribution

As illustrated in Figure 7, art-related discussions exhibit the highest proportion of negative sentiment, indicating public concerns regarding creativity, originality, and ethical implications of Generative AI. In contrast, innovation and cloud-related topics show the highest levels of positive sentiment, reflecting optimism toward technological advancement and practical benefits. Several topics, including education, search, and model, are dominated by neutral sentiment, suggesting that discourse in these areas is largely informational and exploratory rather than evaluative. Detailed sentiment counts for each topic are summarized in Table 13.

Table 13. ABSA results

Topic	Negative	Neutral	Positive
application	5551	7961	4060
art	49555	48258	24922
cloud	353	6340	8861
digital_asset	2006	5277	5691
education	1335	10854	8517
ethics	1792	4108	2425
gadgets	314	800	1285
innovation	4005	27029	32213
model	17043	36852	30770
productivity	1429	1912	1044
search	1353	2392	1532

The sentiment distribution across topics demonstrates that public perceptions of Generative AI are strongly shaped by the specific aspects being discussed. Art-related topics are associated with a higher proportion of negative sentiment, reflecting concerns about originality, copyright, and the potential impact of GenAI on creative work. Conversely, innovation and cloud-related topics are characterized by predominantly positive sentiment, indicating favorable views on efficiency, scalability, and technological progress. Topics such as education, search, and model are largely neutral, suggesting that public engagement in these areas focuses more on information exchange and exploration than on evaluative judgment. These findings highlight the importance of Aspect-Based Sentiment Analysis in capturing nuanced public perceptions that cannot be adequately represented through overall sentiment polarity alone.

Knowledge Discovery

The integration of topic modeling and ABSA yielded an overview of public opinion on Generative AI, organized by different themes and sentiments. The art topic was dominated by negative sentiment, with the emergence of words such as steal, fake, and replace artist, reflecting anxiety over the loss of originality and copyrights due to automation. Conversely, innovation and cloud were more often associated with positive sentiment, reflecting optimism about efficiency and digital modernization.

The digital asset topic exhibited a balanced sentiment distribution, with terms such as NFT and token reflecting enthusiasm for the digital economy, although accompanied by concerns about speculation and fraud. Education and model topics tended to be neutral, indicating the dominance of informative and exploratory discourse.

The ethics topic exhibited a negative trend, driven by issues such as bias and regulation, which underscore public concern about the ethical and regulatory implications of AI. Meanwhile, gadgets and application topics showed polarized opinions, with praise for AI features on smart devices and criticism regarding privacy issues. The productivity and search topics were neutral, representing pragmatic acceptance of AI in functional contexts.

These findings suggest that public responses to Generative AI are highly contextual, varying according to the topics discussed. Technological and innovative aspects tend to be positively received, while social, artistic, and ethical issues trigger greater resistance.

Discussion

The findings of this study confirm that public perceptions of Generative AI are not monolithic but are highly influenced by the specific topics being discussed. Subjects such as art and ethics tend to evoke stronger negative sentiment, reflecting public anxiety about issues of originality, ethical considerations, and copyright infringement. These concerns align with the arguments presented by Geiger (2024) and Desai & Riedl (2024), who highlight the legal and moral challenges posed by GenAI technologies.

This trend is further supported by Miyazaki et al. (2023), whose study on social media discourse revealed that apprehension about GenAI misuse is particularly prominent. Conversely, more technical or utilitarian topics such as innovation and cloud tended to generate positive sentiment. These topics signify public optimism about increased efficiency, scalability, and the potential of GenAI to drive future technological progress. This optimistic stance aligns with the findings of Nurlanuly (2025) and Islam & Greenwood (2024), who suggest that public approval of GenAI is often contingent upon its practical benefits outweighing its risks.

From the perspective of the Technology Acceptance Model, these sentiment patterns can be interpreted as collective expressions of perceived usefulness and perceived risk. Positive sentiment toward innovation-oriented topics indicates a strong perception of utility, while negative sentiment related to ethics and creativity reflects concerns that may inhibit broader acceptance despite technical advantages. This suggests that acceptance of Generative AI is shaped not only by functionality but also by normative and ethical considerations embedded in public discourse.

Topics such as education, model, and search were characterized by neutral sentiment, indicating that discussions in these areas tend to be more informative and exploratory. This indicates that the platform X is not only used for opinion expression but also serves as a channel for knowledge exchange. These findings align with the work of Suhendra & Selly Pratiwi (2024) and Kristianto et al. (2021), who identified X (formerly Twitter) as a dynamic space for public discourse and collective learning. In line with the Diffusion of Innovations theory, such neutral and informational discourse reflects an ongoing process of sense-making in which users seek to understand and evaluate emerging technologies before forming strong evaluative positions.

The knowledge discovery methodology employed in this research, which integrates five topic modeling algorithms with Aspect-Based Sentiment Analysis (ABSA), proved effective in capturing both the thematic and emotional dimensions of public discourse. Among the models tested, BERTopic and NMF exhibited the best topic coherence scores. Meanwhile, ABSA allowed for detailed sentiment interpretation across specific aspects. These findings reinforce the value of combining multiple NLP techniques, as also demonstrated in prior studies by Pratiwi & Tania

(2025) and Pranatawijaya et al. (2024), where similar hybrid approaches successfully unveiled nuanced public perspectives on technological issues.

From an educational perspective, these results have important implications for informatics education and AI literacy. Public concern surrounding ethical and creative aspects of Generative AI highlights the necessity of integrating ethical reasoning, intellectual property awareness, and critical reflection into informatics curricula. At the same time, the prevalence of neutral sentiment in education-related discussions suggests opportunities for educators to use public discourse as a pedagogical resource. In accordance with the TPACK framework, effective use of Generative AI in education requires alignment between technological knowledge, pedagogical strategies, and content understanding, enabling learners to engage with AI tools both critically and responsibly.

Conclusion

This study explored public perceptions of Generative Artificial Intelligence (GenAI) on the social media platform X by integrating multiple topic modeling approaches with Aspect-Based Sentiment Analysis (ABSA) within a knowledge discovery framework. The findings demonstrate that public sentiment toward GenAI is not homogeneous but varies substantially across thematic and aspectual dimensions.

Addressing the first research question, the analysis identified several dominant topics in public discourse on GenAI, including innovation, cloud services, education, language models, art, and ethical issues. The comparative evaluation of five topic modeling techniques revealed that embedding-based and matrix factorization approaches produced more coherent and interpretable topics in short-text social media data, highlighting the value of multi-model analysis for large-scale public perception studies.

In response to the second research question, sentiment analysis results showed clear variation across topics and aspects. Discussions related to innovation and cloud technologies were predominantly associated with positive sentiment, reflecting optimism regarding efficiency and technological advancement. In contrast, topics related to art and ethics were characterized by higher levels of negative sentiment, indicating public concern over originality, copyright, and responsible use. Education-related discussions were largely neutral, suggesting that social media serves not only as a space for opinion expression but also as a platform for information sharing and exploratory dialogue.

Regarding the third research question, the findings have important implications for informatics education. Public concerns expressed through negative sentiment, particularly in ethical and creative domains, underscore the need to strengthen AI literacy, ethical awareness, and critical evaluation skills within informatics curricula. At the same time, the prevalence of neutral sentiment in education-related discussions indicates opportunities for educators to leverage public discourse as a pedagogical resource, supporting informed and reflective engagement with GenAI technologies.

From a theoretical perspective, the results align with technology adoption and diffusion frameworks by illustrating how perceived benefits, perceived risks, and social communication channels shape public attitudes toward emerging technologies. Rather than serving as predictive models, these frameworks provide a conceptual basis for interpreting how public sentiment reflects acceptance, resistance, and readiness for GenAI adoption in educational contexts.

Several limitations should be acknowledged. Data collection was limited to English-language tweets and subject to a daily retrieval cap, which may affect representativeness and overlook short-term discourse spikes. In addition, although transformer-based sentiment classification demonstrated reliable performance, challenges such as sarcasm, implicit sentiment, and contextual ambiguity remain inherent limitations in social media text analysis. Future research may extend this work by incorporating multilingual data, cross-platform analysis, and more advanced aspect modeling techniques.

Overall, this study contributes methodologically by demonstrating the effectiveness of combining multi-model topic modeling with aspect-based sentiment analysis, and substantively by providing empirical insights into public perceptions of Generative AI. These insights support informed decision-making for AI literacy development, curriculum design, and responsible integration of GenAI within informatics education.

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