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Sentiment Dynamics of Generation Z in Online Firestorms: A Twitter-Based Analysis of Brand Misconduct

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ABSTRACT

This study examines Generation Z's negative electronic word-of-mouth (e-WOM) during the 2022 Harvard Business School (HBS) "Online Connext" X firestorm. Of the 3,898 analyzed tweets, 69% (2,688) expressed negative sentiment, primarily driven by ethical and ideological concerns. A novel hybrid framework integrating BERTopic topic modeling and hashtag analysis identified three dominant themes, ideology, ethics, and leadership, and revealed how #HBSONLINECONNEXT coordinated collective outrage. Support Vector Machine (SVM) achieved 90% accuracy in sentiment classification. Findings underscore Generation Z's ethical sensitivity and strategic use of hashtags to amplify reputational crises. We recommend real-time hashtag monitoring, transparent communication, and theme-specific crisis responses. This interdisciplinary study bridges marketing, consumer behavior, and data science, providing a scalable tool for analyzing digital activism.

Keywords: Generation Z, e-WOM, Online Firestorms, BERTopic, Hashtag Analysis, Brand Crisis, Sentiment Analysis

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1. INTRODUCTION

Social media has fundamentally reshaped how Generation Z responds to brand misconduct, with platforms such as X (Formerly Twitter) serving as powerful amplifiers of negative sentiment during online firestorms [1]. These crises typically emerge from perceived ethical or ideological violations and spread rapidly through hashtags and viral content loops, often inflicting severe reputational harm on brands [1-2]. Although positive electronic word-of-mouth (e-WOM), such as expressions of brand loyalty, has been widely examined [3], negative e-WOM, particularly forms driven by brand hate and hashtag-fueled outrage, remains comparatively underexplored, especially among Generation Z [4].

Despite the expanding body of research on e-WOM and digital firestorms, three critical gaps persist. First, Generation Z, known for its digital fluency and pronounced ethical awareness, has received limited scholarly attention. Second, the role of hashtags as mechanisms of coordination and amplification in negative e-WOM is underexamined. Third, few studies integrate thematic content analysis with structural dynamics to provide a holistic understanding of online firestorms [5-6]. This study addresses these gaps by analyzing the 2022 Harvard Business School (HBS) "Online Connext" controversy, an X firestorm triggered by perceived ideological bias in a keynote speech. Drawing on a dataset of 3,898 unique tweets (after removing 36 duplicates), we investigate emotional triggers, thematic clusters, and hashtag coordination patterns. To achieve this, we propose a novel hybrid analytical framework that integrates BERTopic for topic modeling and hashtag analysis for coordination mapping. BERTopic captures the semantic richness of online discourse, while hashtag analysis uncovers structural dynamics and user collaboration. Together, these approaches provide a comprehensive understanding of firestorm dynamics.

Our study contributes to the literature in three major ways. (1) We introduce an innovative hybrid framework integrating BERTopic topic modeling with hashtag analysis to capture both semantic themes and structural coordination in negative e-WOM. (2) We provide empirical evidence of Generation Z's values-driven ethical activism and strategic hashtag use in brand crises. (3) We propose actionable, theme-specific crisis response strategies, including real-time hashtag monitoring.

The paper is structured as follows: Section 2 reviews the relevant literature on e-WOM, online firestorms, and Generation Z activism. Section 3 outlines the methodology, including data collection and modeling procedures. Section 4 presents the results on sentiment, thematic patterns, and hashtag dynamics. Section 5 discusses the findings and their implications, and Section 6 concludes the study.

2. LITERATURE REVIEW

The advent of social media has profoundly transformed consumer-brand interactions, empowering digitally native generations like Generation Z to amplify their voices in real time and escalate brand crises into global spectacles. Platforms such as X serve as critical arenas for e-WOM, where concise, hashtag-driven communications can rapidly mobilize collective outrage or solidarity [7-9]. This review synthesizes foundational and emerging research on social media dynamics, e-WOM mechanisms, brand transgressions, online firestorms, and Generation Z's distinctive activism. Social media's architecture has democratized communication, enabled instantaneous global connectivity and turned platforms into amplifiers of consumer sentiment [7]. X's 280-character constraint fosters succinct, emotionally charged exchanges, while features like retweets and hashtags facilitate viral propagation and thematic organization, as evidenced in campaigns such as #MeToo [7-9]. These mechanics not only enhance engagement but also intensify the stakes for brands, where a single misstep can cascade into reputational erosion [10-12].

Within this ecosystem, e-WOM emerges as a pivotal force: online dissemination of opinions, reviews, or experiences that shape perceptions and behaviors [10]. Positive e-WOM builds trust and loyalty. Research indicates that 70% of consumers equate online reviews with personal recommendations [10], often modeled through frameworks like the Theory of Consumption Value to predict purchase intent [3]. However, negative e-WOM exhibits asymmetric potency, eroding relationships far more swiftly and enduringly, especially when tied to ethical lapses or ideological clashes [11-12].

Brand transgressions, violations of expected norms, whether ethical, social, or ideological, ignite negative emotions that culminate in brand hate, a visceral aversion driving criticism, avoidance, or active sabotage [13]. These infractions disrupt relational bonds, transforming passive dissatisfaction into vocal dissent [14]. When amplified online, they fuel brand hate's expression through e-WOM, where consumers not only vent but also seek accountability [13-14].

Online firestorms represent the apex of this escalation: sudden, explosive surges of negative feedback that demand swift institutional responses [15]. Hashtags act as linchpins, coordinating disparate voices into unified narratives and sustaining momentum, as seen in the 2018 Starbucks racial profiling incident, which birthed #BoycottStarbucks and prompted policy overhauls [16-17]. Despite growing scholarship on firestorms' mechanisms and impacts [15-16], the interplay of emotional triggers with structural elements like hashtags remains underexamined, especially in ideologically charged contexts where legal actions do not preclude perceptual backlash [17].

Generation Z (born 1997-2012) embodies this digital upheaval as true natives, immersed in technology from infancy and wielding platforms with strategic acumen [15,18]. Their ethical vigilance, prioritizing corporate responsibility, social justice, and authenticity, propels activism that transcends individual grievance, manifesting in hashtag-orchestrated movements like #FridaysForFuture for climate action [19]. In brand contexts, Gen Z's responses to misconduct are swift and collective, converting personal outrage into campaigns that enforce accountability and influence market outcomes [19-20].

Analytical advancements in natural language processing (NLP) and machine learning have equipped researchers to dissect these phenomena with precision. Topic modeling like Latent Dirichlet Allocation (LDA) uncovers latent themes in unstructured data [21]. Sentiment analysis classifies textual polarity [22], while BERT-based innovations enhance nuance in short-form texts, though applications to tweets lag [23]. Hashtag analysis illuminates' coordination networks [21,23].

However, siloed approaches prevail: few integrate semantic topic discovery with structural hashtag mapping to holistically capture firestorm evolution, particularly Gen Z's role [5-6]. Synthesizing these strands, the literature illuminates social media's amplification of e-WOM, the perils of transgressions fostering brand hate, and firestorms' hashtag-fueled trajectories, with Gen Z as ethical vanguard [13]. Critical voids endure: (1) negative e-WOM's escalation via Gen Z's activism, beyond positive loyalty foci [3,10]; (2) younger demographics' unique patterns in firestorms [15,18]; and (3) hybrid methods merging advanced modeling (e.g., BERT) with hashtag dynamics for dual content-structure insights [21,23]. This study redresses them through a novel hybrid framework fusing BERTopic, for semantically rich, coherent themes in informal tweets, with hashtag analysis to map coordination and amplification. Exemplified in the HBS "OnlineConnext 2022" firestorm, it empirically delineates Gen Z's sentiment triggers, thematic clusters (ideology, ethics, leadership), and strategic hashtag deployment (e.g.,

#HBSONLINECONNEXT). Advancing beyond conventional tools, this integration yields granular, actionable views of firestorm interplay, enriching interdisciplinary theories and equipping brands for ethical navigation in a Gen Z-dominated landscape. The ensuing methodology operationalizes this framework to probe these dynamics empirically.

3. METHODOLOGY

This study adopts the cross-industry standard process for data mining (CRISP-DM) [24] framework to ensure a systematic, reproducible, and comprehensive analysis of Generation Z's negative e-WOM during the 2022 HBS "Online Connext" X firestorm. The six-phase CRISP-DM model, Business Understanding, Data Understanding, Data Preparation, Modeling, Evaluation, and Deployment, provides a structured pathway from problem definition to actionable insights, as illustrated in Figure 1.

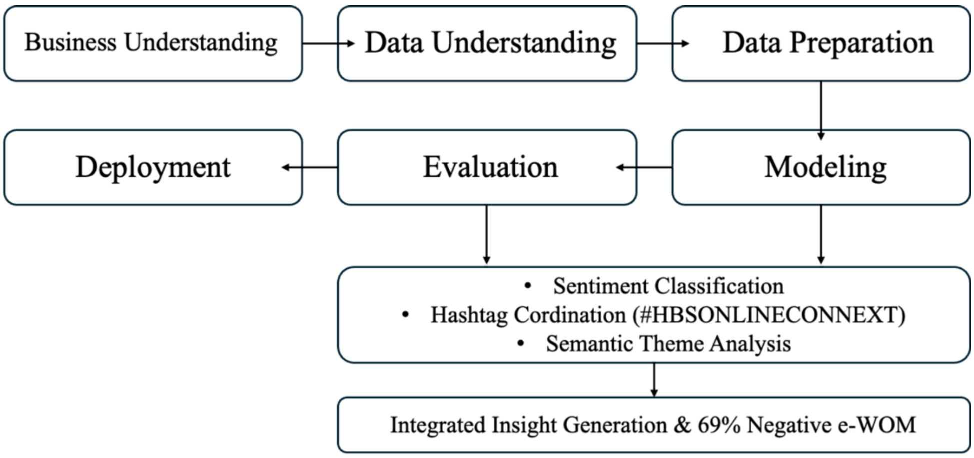


Figure 1. Proposed methodology of the study

Figure 1 visually maps each phase of this study to the CRISP-DM lifecycle, illustrating the iterative and interconnected nature of the analytical process.

3.1 Business and Data Understanding

The Business Understanding phase established the research objectives and contextual scope. The primary goal was to investigate how Generation Z expresses and coordinates negative sentiment during brand crises on social media, using the HBS "Online Connext 2022" controversy as a focal case [25]. This event, held on May 14, 2022, was a hybrid leadership conference themed "Reimagining Leadership", designed to explore post-pandemic business innovation and organizational resilience. However, a keynote address by Professor Julie Battilana, perceived by many as promoting left-leaning ideological frameworks, ignited widespread backlash, particularly among Gen Z users [26]. Critics accused HBS of injecting political bias into business education, prompting calls for institutional accountability and ideological neutrality. The Data Understanding phase involved identifying, sourcing, and exploring relevant social media data. X was selected as the primary platform due to its real-time discourse, hashtag-driven coordination, and high engagement among digital natives. With over 230 million daily active users and a 280-character limit per tweet, X facilitates rapid, emotionally charged, and structurally organized communication, ideal for studying firestorm dynamics. Data collection was conducted using Tweed, a robust open-source Python library for X scraping that operates without requiring authenticated API access, a critical advantage given X's post-2022 restrictions on free-tier API usage. A targeted keyword strategy was employed, combining event-specific terms ("onlineconnext2022"), institutional identifiers ("HarvardHBS"), and domain descriptors ("business school"). The collection window spanned from May 14, 2022, to August 14, 2022, capturing both the initial outrage and its three-month evolution. A total of 3,934 tweets were retrieved. After removing 36 exact duplicates via string matching, 3,898 unique tweets remained for analysis. Collected attributes included full tweet text, engagement metrics (likes, retweets, replies), and timestamps. Usernames and personally identifiable information were excluded to ensure compliance with ethical standards and privacy regulations.

3.2 Data Preparation

The data preparation phase transformed the raw collection of 3,934 tweets into a structured, analysis-ready dataset comprising 3,898 unique records after the removal of 36 exact duplicates identified through string matching, a critical step to prevent overrepresentation of identical expressions in subsequent modeling. This cleaned corpus, representing 99.1% of the original data, was then processed using Python's Natural Language Toolkit (NLTK) with a custom preprocessing pipeline tailored to the linguistic and structural characteristics of X discourse. Tokenization was performed using NLTK's Tweet Tokenizer, which preserved hashtags, user mentions, URLs, and emojis as integral semantic units rather than fragmenting them, while all text was converted to lowercase to ensure case-insensitive analysis. Part-of-speech tagging followed, leveraging a X-specific POS tagger [27] adapted from the ARK Social Media framework, enabling accurate identification of retweet markers ("RT"), elongated expressions, and sentiment-bearing emojis, thereby enriching contextual understanding beyond standard grammatical roles. A curated stop word list was applied, combining conventional English stop words with platform-specific noise terms such as “rt”, “via”, and generic event fillers like “live” or “join”, while retaining punctuation marks associated with emotional intensity (e.g., multiple exclamation or question marks) in a parallel feature channel. Lemmatization using WordNet with POS guidance reduced inflectional variants without aggressive stemming that could obscure meaning in short-form text, ensuring semantic fidelity. Emojis were mapped to sentiment polarity scores based on the Emoji Sentiment Ranking, allowing their integration as quantitative emotional signals. Feature engineering produced dual representation streams: TF-IDF matrices for traditional machine learning models and GloVe X pretrained embeddings (100-dimensional) for deep learning and topic modeling components. Hashtags and mentions were extracted into dedicated fields to support structural coordination analysis. The preprocessing sequence progressively refined the dataset, with duplicate removal eliminating 0.9% of the initial volume, tokenization and filtering enhancing signal clarity, and final feature generation yielding a compact, high-quality dataset optimized for sentiment classification, topic discovery, and hashtag network analysis, with all intermediate outputs logged for reproducibility and auditability**.**

3.3 Modeling

In the modeling phase, a comprehensive suite of machine learning, deep learning, and topic modeling techniques was applied to analyze sentiment polarity and thematic structures within tweets. The selected models, Random Forest (RF), Naive Bayes (NB) [28], Support Vector Machine (SVM) [29], Logistic Regression (LR), Long Short-Term Memory (LSTM), Recurrent Neural Network (RNN) [30], and BERTopic [31], were chosen for their complementary capabilities in classification, sequence modeling, and unsupervised topic discovery.

- ***Sentiment Classification Models***

Both traditional and neural approaches were implemented for sentiment classification. Random Forest, an ensemble learning method, constructs multiple decision trees based on random subsets of data and features, combining results via majority voting to mitigate overfitting. Naive Bayes, grounded in Bayes’ theorem, assumes feature independence and performs efficiently with high-dimensional TF-IDF text inputs [32]. SVM identifies the optimal hyperplane that maximizes class separation, employing kernel functions such as

RBF to capture non-linear relationships. Logistic Regression, serving as a baseline linear model, estimates class probabilities using a logistic function optimized through maximum likelihood estimation. For sequential data, LSTM networks, with their gated memory architecture, effectively capture long-term dependencies in text embeddings. RNNs, in contrast, process sequential data by maintaining a hidden state that captures contextual information from previous time steps, enabling the modeling of temporal dependencies and sentiment progression in text.

- ***Topic Modeling with BERTopic***

Unsupervised topic discovery was conducted using BERTopic, which generates contextual embeddings through pre-trained BERT models, reduces dimensionality with UMAP, clusters documents via HDBSCAN, and extracts topic representations using class-based TF-IDF (c-TF-IDF). The c-TF-IDF score for a word w in topic t is calculated as Formula 1 [33]:

$$\mathrm{C-TF-IDF}(w,t) = \mathrm{TF}(w,t)\ .\ \log\left(\frac{\mathrm{N}}{\mathrm{DF}(w)}\right),$$

Formula 1

Where TF(w,t) denotes the frequency of word w in topic t, DF(w) represents its document frequency across all topics, and N is the total number of documents. Inter-topic relationships were visualized through distance maps, while hashtags were analyzed separately to examine coordination dynamics. These two analyses were subsequently integrated to link thematic content with structural user behavior.

- ***Evaluation Metrics***

Model performance was assessed using standard evaluation metrics [30]:

1) Accuracy, Proportion of correct predictions:

$$Accuracy = \frac{TruePositives + TrueNegatives}{TotalPredictions}$$

2) Precision: Proportion of true positive predictions among all positive predictions:

$$Precision = \frac{TruePositives}{TruePositives + FalsePositives}$$

3) Recall: Proportion of true positives identified among all actual positives:

$$Recall = \frac{TruePositives}{TruePositives + FalseNegatives}$$

4) F1-Score: Harmonic mean of precision and recall:

$$F1 - Score = 2.\frac{Precision.Recall}{Precision + Recall}$$

5) AUC-ROC: Area under the receiver operating characteristic curve (1.0 = perfect, 0.5 = random).

- ***For BERTopic, topic quality was assessed using:***

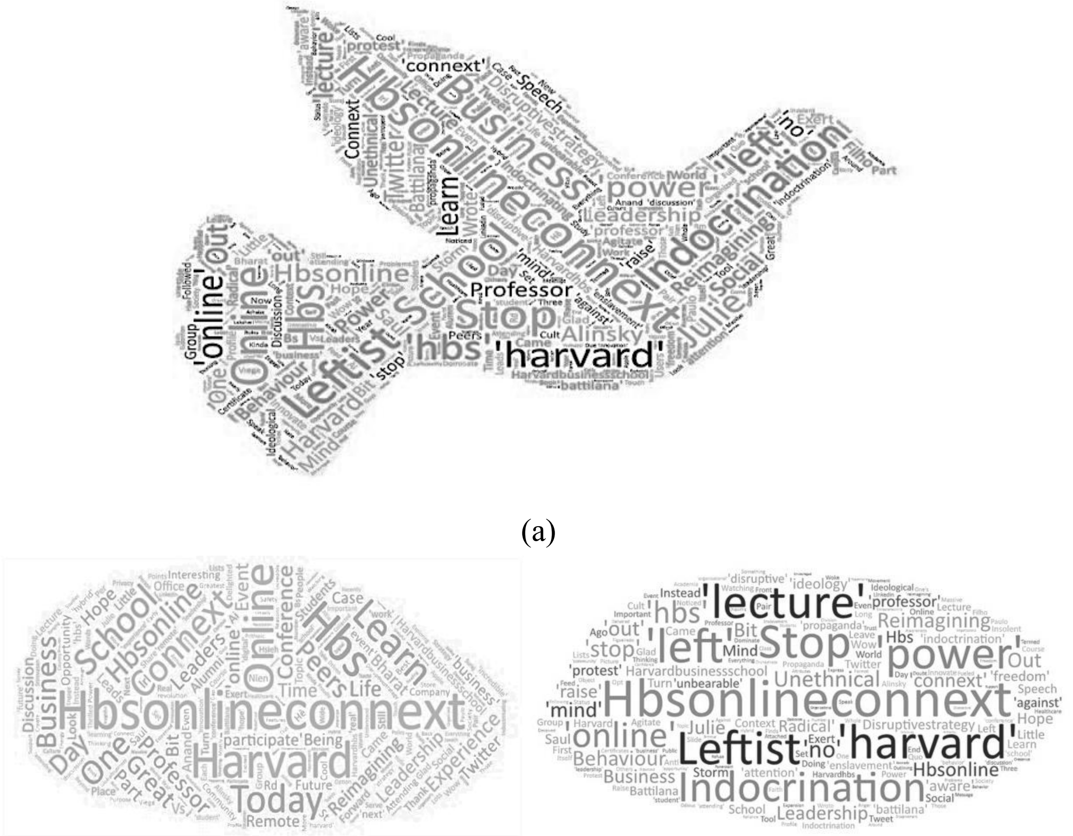
- **UMass Coherence:** Measures word co-occurrence within the corpus.
- **CV Coherence:** Evaluates topic interpretability via NPMI, with values closer to 1 indicating stronger semantic cohesion and greater interpretability. Higher UMass (less negative) and CV scores reflect better topic quality.

This multi-metric approach ensured both robust sentiment classification and interpretable topic discovery, forming a reliable foundation for the integrated analysis of content and coordination within the online firestorm.

4. MODEL PERFORMANCES AND ANALYTICAL INSIGHT

4.1 Word Frequency and TF-IDF Analysis

Word frequency analysis, as shown in Figure 2, revealed polarized language. Negative tweets frequently used "ideology," "propaganda," "woke," and #HBSONLINECONNEXT, signaling coordinated protest. Positive tweets featured "dynamic," "innovation," and "freedom," showing support for the event's goals.



(a)

(b) (c)

Figure 2. Word clouds of most frequent terms in (a) all tweets, (b) positives, (c) negatives

The study also utilized the TF-IDF algorithm to evaluate the significance of words based on Term Frequency (TF), which measures how frequently a word appears in a specific document, and Inverse Document Frequency (IDF), which assesses the rarity of a word across all documents. The key findings from the word frequency analysis are summarized in Table 1.

Table 1. Top 15 words by TF-IDF score in positive vs. negative tweets

Category	**Most Frequent Words**	**Insights**
All Tweets	hbs, online, Harvard, business, school	These terms reflect significant user engagement, indicating active discussions about Harvard Business School’s online initiatives on X
Negative Tweets	left, ideology, propaganda, power, aware, stop, woke, lecture, enslavement	These words suggest dissatisfaction with a professor’s speech, with “woke” and “aware” signaling coordinated protests. Terms like “enslavement” and “power” highlight skepticism and negative sentiment toward perceived ideological coercion
Positive Tweets	dynamic, realistic, discussion, leadership, innovation, freedom, social, online, business, share	These terms convey optimism and support for Connext2022, emphasizing leadership, innovation, and post-pandemic business opportunities. “Freedom” underscores the value of free speech and open dialogue

As shown in Table 1, in negative tweets, high-TF-IDF terms like “left,” “ideology,” “propaganda,” and “woke” were frequently paired with #HBSONLINECONNEXT, indicating a coordinated protest against perceived ethical or ideological issues, driving negative e-WOM. Users viewed certain actions as coercive, with terms like “enslavement” and “power” reflecting distrust toward brands. [34] notes that acknowledging mistakes and demonstrating transparency are vital for rebuilding consumer trust, emphasizing the need for strategic apologies to address negative sentiment. Conversely, positive tweets featured words such as “dynamic,” “discussion,” “innovation,” and “freedom,” signaling enthusiasm for Connext2022 as a platform for exploring post-pandemic business opportunities. The term “freedom” highlighted the importance of free expression, with users valuing open dialogue despite controversies. Analysis of tweet length over time showed that during the storm’s peak, users maximized X’s 280-character limit to express strong emotions. As emotional intensity subsided, tweet length and word count decreased, reflecting calmer discourse. By combining word frequency analysis, TF-IDF, and word cloud visualizations, this study revealed insights into digital natives’ sentiments. Negative tweets underscored coordinated protests and dissatisfaction, while positive tweets conveyed optimism and support for the event's broader goals, highlighting the critical role of strategic communication and transparency in managing brand perception and restoring trust amid public criticism.

4.2 Hashtag and Keyword Analysis

Hashtag and keyword analysis revealed the triggers of the X firestorm. As shown in Table 2, "unethical behavior" (645 mentions) was the main source of outrage, highlighting concerns about organizational ethics. These findings show how hashtags amplified Gen Z's reactions to perceived brand misconduct. Even when companies act legally, user concerns can still spark online backlash and damage brand relationships.

Table 2. Frequency of trigger keywords by category (N = 3,898)

Category of Online Firestorm Triggers	No. of Occurrences
Unethical Behavior	645
Business-Related Issues	125
Communication Behavior	87

Key insights from Table 2 indicate that Business-related issues and communication behaviors also contributed significantly, with 125 and 87 mentions, respectively, highlighting additional sources of user frustration. These findings emphasize that digital natives' perceptions of ethical violations, operational missteps, and communication failures act as critical sparks for coordinated social media protests. Hashtags play a pivotal role on X, enabling users to categorize content, connect with others, and amplify specific messages. An analysis of hashtag usage revealed that 29% of Generation Z tweets (781 tweets) included the hashtag #HBSONLINECONNEXT, demonstrating a structured and unified campaign among digital natives. This strategic use of hashtags reflects their intent to elicit a response from the targeted brand while fostering a cohesive movement to avoid fragmented communication. Table 3 lists the most popular hashtags used by digital natives.

Table 3. Top 10 hashtags by frequency in generation Z tweets

Number of Occurrences	Hashtag
781	#HBSONLINECONNEXT
378	#ReimaginingLeadership
189	#unethnical_behavior
42	#HarvardBusinessSchool
36	#HBSOnline
19	#disruptivestrategy

As illustrated in Table 3, the dominant use of #HBSONLINECONNEXT highlights an organized effort to focus attention on grievances against the brand, while other hashtags, such as #ReimaginingLeadership and #unethnical_behavior, reflect themes of leadership, ethics, and strategic disruption. These findings highlight how digital natives leverage hashtags to channel outrage, share perspectives, and drive collective action, creating a unified front to demand accountability and change.

4.3 Topic Modeling

Topic modeling helps uncover semantic patterns in text and is widely used in NLP tasks like sentiment analysis. In this study, BERTopic was applied to identify key discussion themes in tweets from digital natives. The process involves three steps: converting each tweet into embeddings with a pre-trained model, reducing embedding dimensions for efficient clustering, and extracting thematic representations from clusters using a customized TF-IDF approach.

- ***Inter-topic Distance Maps***

Inter-topic distance maps are tools used to visualize the relationships between different topics in a text collection. These maps help illustrate the similarity or dissimilarity between topics and can be used to identify clusters of related topics (See Figure 3).

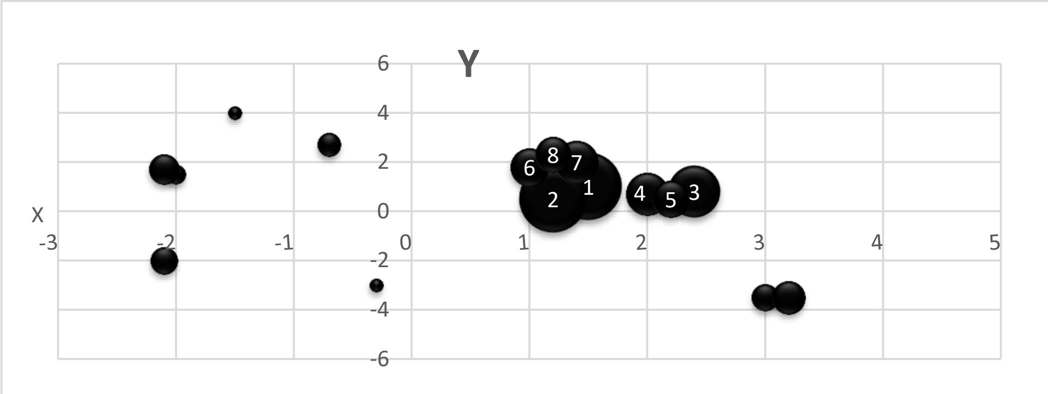


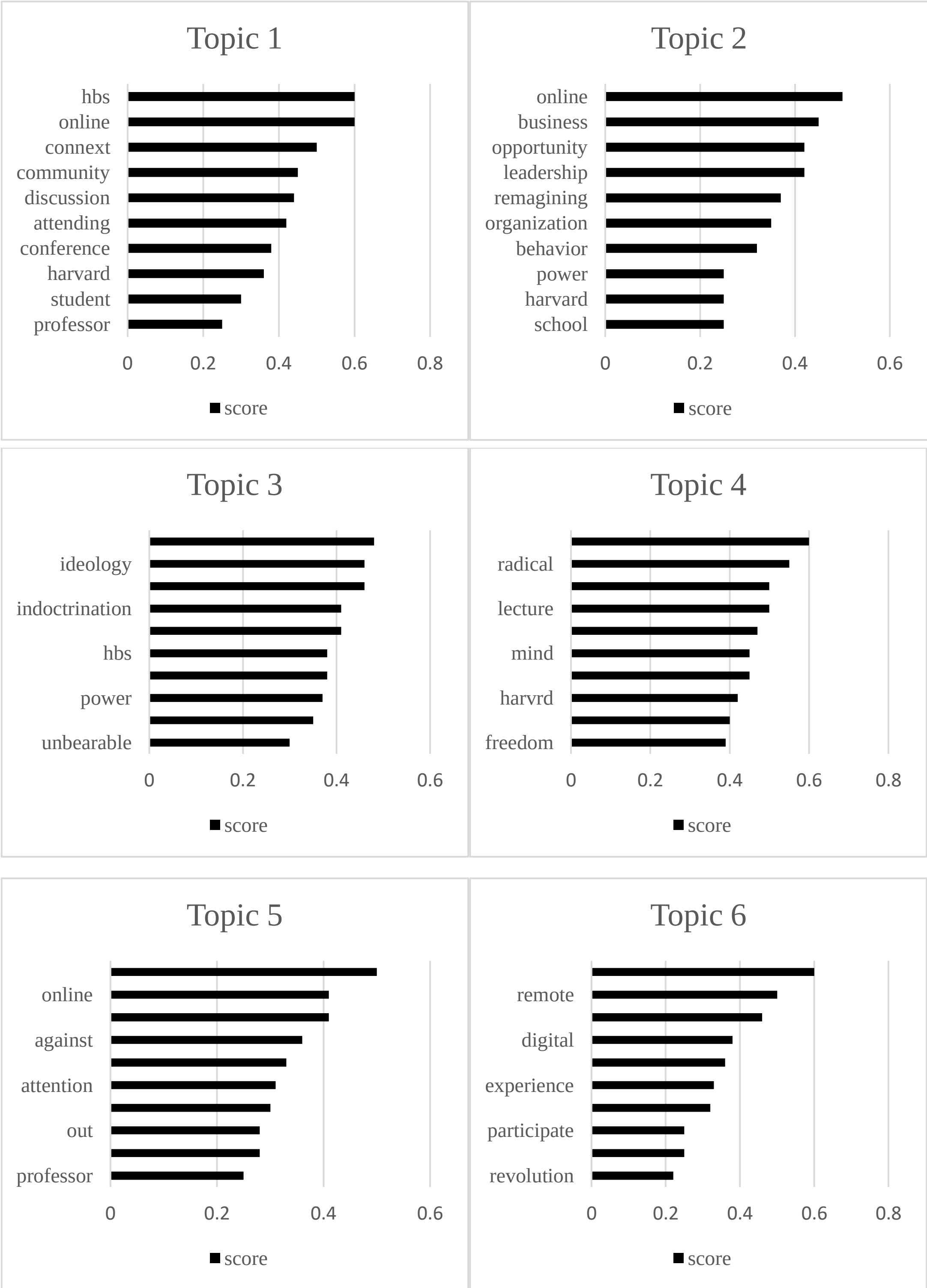
Figure 3. Inter-topic distance map (UMAP + HDBSCAN) of BERTopic clusters

As shown in Figure 3, the inter-topic distance map reveals that Topic 1 (ideology) is closely related to Topic 4 (ethics), indicating overlapping discussions among Generation Z. Based on topic similarities, eight closely related and well-defined themes were identified. These topics reflected themes from the Harvard School Conference, such as leadership, organizational behavior, online business, and digital experience, and included both positive sentiments (e.g., hybrid event, participating student, next conference) and negative ones (e.g., stop lecture, left ideology, radical, power). The topics were clustered using HDBSCAN, as summarized in Table 4.

Table 4. BERTopic clusters: top 8 topics with representative terms and coherence scores

Topic- Count- Percent	**Name**	**Representation**
Topic1-628-%0.26	1_ hbs_online_ connect_ community	'hbs', 'online', 'connect', 'community', 'discussion', 'attending', 'conference', 'Harvard', 'student', 'professor'
Topic2-425-%0.18	2_online_business_ opportunity leadership	'online', 'business', 'opportunity', 'leadership', 'reimagining', 'organizational', 'behavior', 'power', 'Harvard', 'school'
Topic3-301-%0.13	3_ stop _ ideology _ left indoctrination	'stop', 'ideology', 'left', 'indoctrination', 'propaganda', 'hbs', 'lecture', 'power', 'protest', 'unbearable'
Topic4-293-%0.12	4_ left _ radical _ power lecture	'left', 'radical', 'power', 'lecture', 'disruptive', 'mind', 'enslavement', 'Harvard', 'aware', 'freedom'
Topic5-260-%0.11	5_connext _online Harvard_ against	'connext', 'online', 'harvard', 'against', 'no', 'attention', 'raise', 'out', 'battilana', 'professor'
Topic6-192-%0.08	6_learning_remote _ business digital	'learning', 'remote', 'business', 'digital', 'work', 'experience', 'online', 'participate', 'incredible', 'revolution'
Topic7-156-%0.06	7_online_hope_nex t_ conference	'online', 'hope', 'next', 'conference', 'future', 'innovation', 'leadership', 'business', 'real', 'strategy'
Topic8-120-%0.05	8_hbs_online_hybr id_ event	'hbs', 'online', 'hybrid', 'event', 'discussion', 'attending', 'Harvard', 'school', 'student', 'participate'

The term "online" appears prominently across multiple topics due to the event name "OnlineConnext," but global word frequency analysis (Figure 2) reveals #HBSONLINECONNEXT, Harvard, and leadership as the most frequent terms overall. Figure 4 also illustrates users' positive and negative sentiments toward the identified topics.


Topic 1
hbs
online
connext
community
discussion
attending
conference
harvard
student
professor
0
0.2
0.4
0.6
0.8
score
Topic 2
online
business
opportunity
leadership
remagining
organization
behavior
power
harvard
school
0
0.2
0.4
0.6
score
Topic 3
ideology
indoctrination
hbs
power
unbearable
0
0.2
0.4
0.6
score
Topic 4
radical
lecture
mind
harvrd
freedom
0
0.2
0.4
0.6
0.8
score
Topic 5
online
against
attention
out
professor
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0.2
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Topic 6
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digital
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participate
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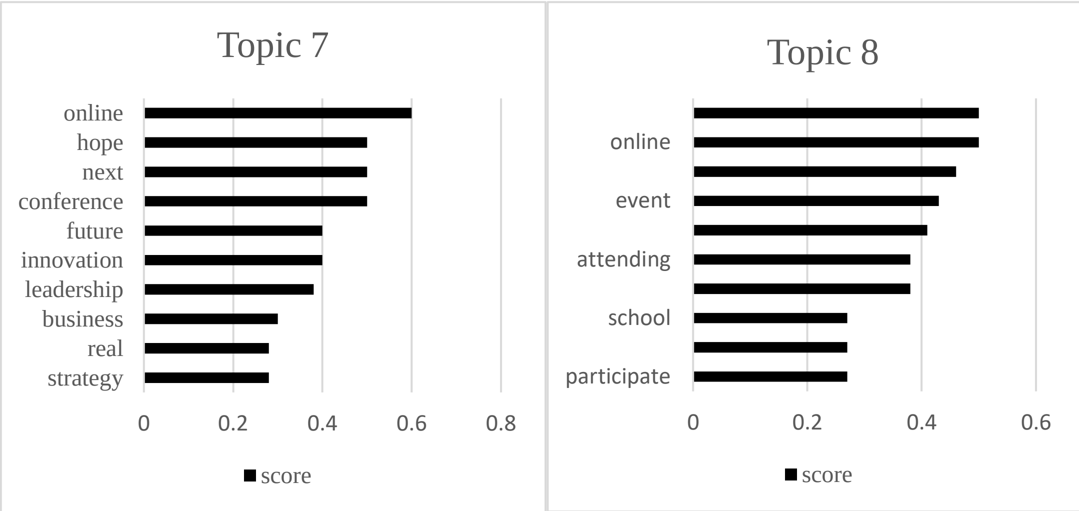


Figure 4. Average sentiment polarity score by BERTopic cluster

The majority of sentiments expressed were negative, particularly in Topics 1, 3, 4, and 5, where negative sentiments predominated. For instance, in Topic 1, more than 60% of digital natives expressed negative emotions regarding the HBS event. However, Topics 6, 7, and 8 exhibited more positive sentiments. Figure 5 also illustrates the percentage breakdown of user sentiments by topic.

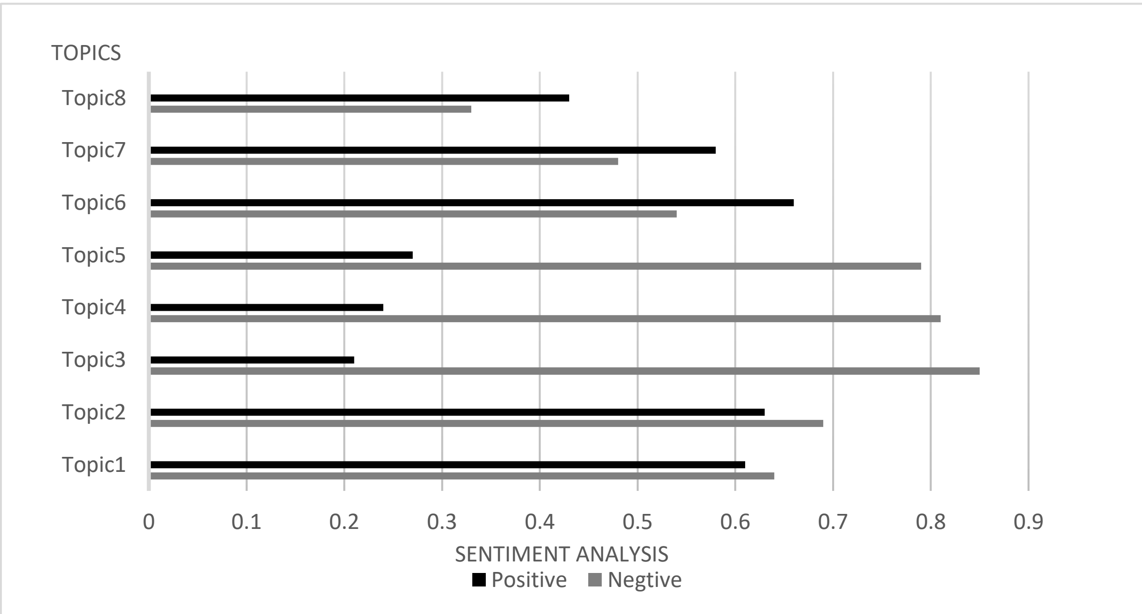


Figure 5. Sentiment distribution (% positive vs. % negative) across BERTopic clusters

Figure 5 illustrates the percentage breakdown of positive vs. negative sentiments across BERTopic clusters. Negative sentiment dominates in Topics 1, 2, 3, 4, and 5, while Topics 6-8 show stronger positive polarity.

- ***Results of Topic Analysis***

Topic modeling identified clusters of words defining distinct topics within the tweet dataset. Using BERTopic, we estimated the likelihood of words or phrases belonging to specific topics, clustering tweets based on semantic similarity. The coherence score, which measures topic interpretability, highlighted topics with the strongest word associations (see Figure 6).

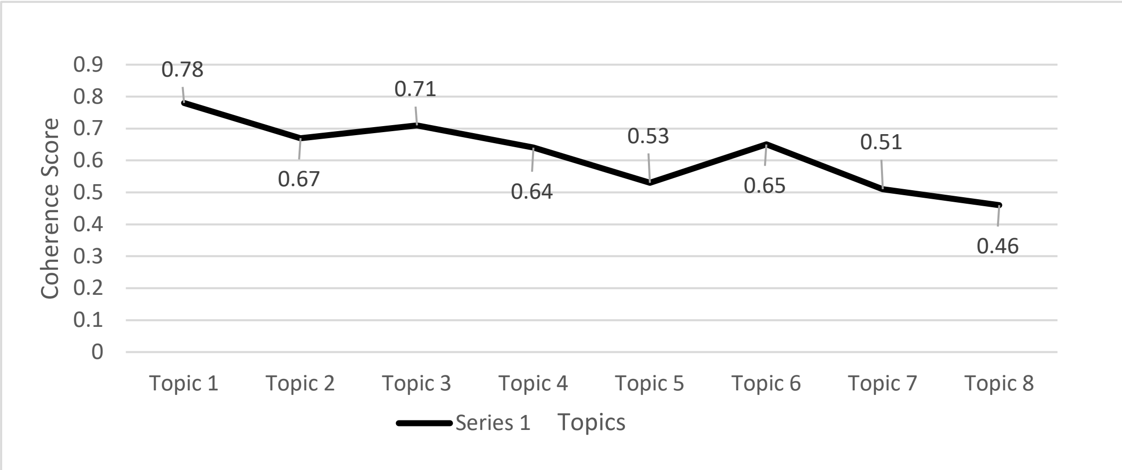


Figure 6. Topic coherence scores (UMass and CV) for top 8 BERTopic clusters

As shown in the figure above, Topic 1 (ideology) achieved the highest coherence scores (UMass and CV), indicating the strongest internal word associations.

4.4 Interaction and Sentiment Analysis

Word embedding, a key NLP concept, represents words as real-valued vectors, allowing semantically similar words to appear close together in the embedding space. In this study, the Gensim library in Python was used to generate embeddings from the dataset. The analysis showed that terms like “leftism,” “ideology,” “propaganda,” and “rightism” clustered together, reflecting shared conceptual themes. Similarly, words such as “power,” “leadership,” “lecture,” and “discussion” appeared closely related, indicating their contextual connections. Vocabulary such as “social,” “online,” “business,” and “school” also formed tight clusters, showing semantic relationships within tweets. Figure 7 visualizes these vector distributions and proximities.

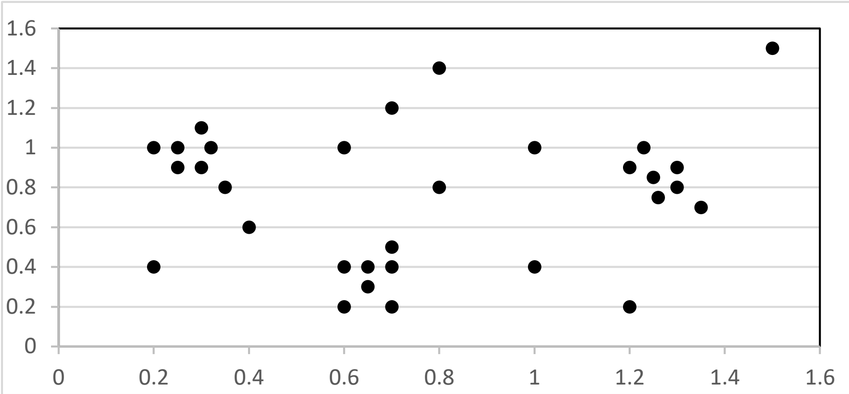


Figure 7. 2D word embedding visualization (t-SNE) of top 50 high-TF-IDF terms

The figure above emphasizes the meaningful relationships and shared contexts among these terms in the tweets analyzed. In this study, descriptive analysis of the data was conducted using the Scikit-Learn and Matplotlib libraries in Python. After identifying outlier data, removing duplicate words and stopwords, and tokenizing the data, the obtained texts were manually labeled as positive, negative, or neutral. Tweets that were repetitive or did not provide useful information related to the topic were excluded, leaving a total of 3,898 tweets for analysis. Table 5 presents sample tweets for each sentiment category (positive, negative, neutral).

Table 5. Sample tweets by sentiment category

Sample Tweets	Manual Analysis
The ideological propaganda in the most important business school in the world.	Positive
I came to @HarvardHBS hoping to learn a little bit about…business. Instead, I'm watching a lecture by Saul Alinsky on how to exert leftist power. Wow! Leftists turn EVERYTHING into ideological propaganda	Negative
The new order, the leftopathy, in full swing	Neutral
Take it easy and Listen to the rest of the speech	Neutral

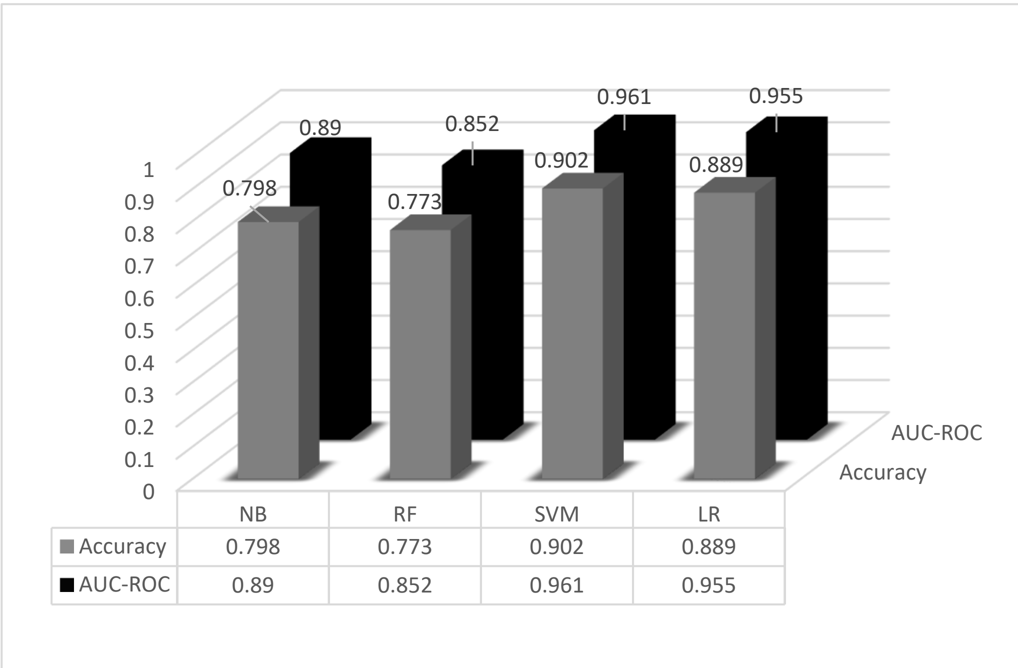
Out of 3,898 tweets, 2,688 (69%) were negative, 826 (21%) positive, and 384 (10%) neutral. The number of tweets expressing negative sentiments is significantly higher than that expressing positive sentiments. This indicates the presence of online anger among digital natives and negative word-of-mouth due to brand misconduct. However, some positive opinions suggest that some digital natives still feel an attachment to the brand, with some showing a degree of forgiveness. Analyzing the number of positive and negative tweets provides insights into the challenges and opportunities brands face during online storms.

Table 6. Sentiment distribution across 3,898 tweets

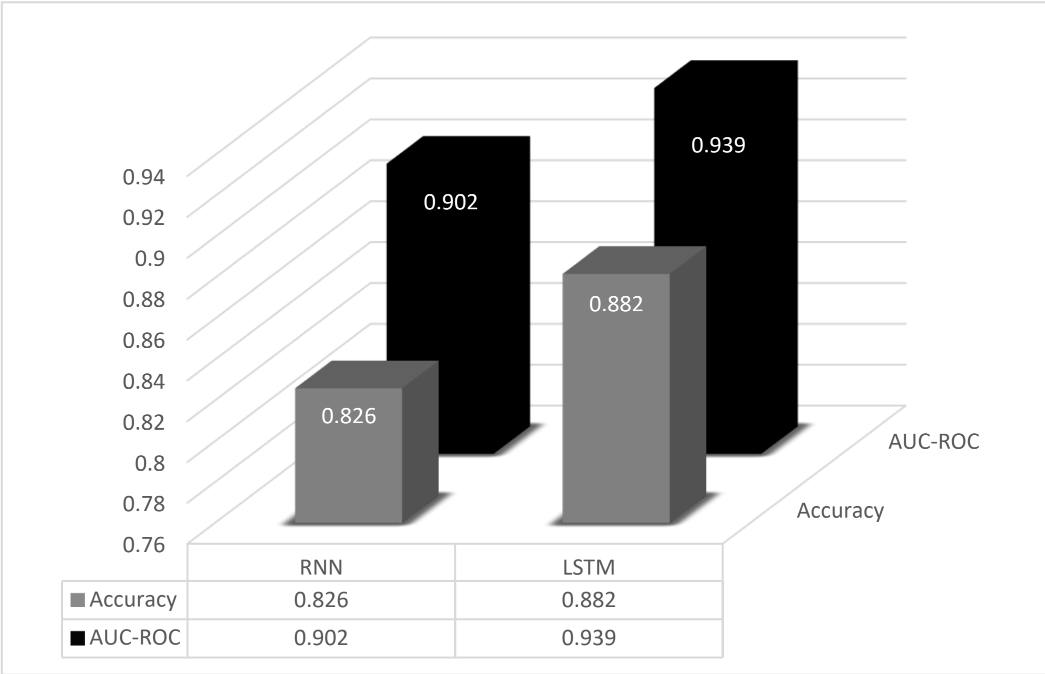
Type of Interaction	Tweets
Most Likes	The ideological propaganda in the most important business school in the world
Most Retweets	Stop the leftist indoctrination at #HBSONLINECONNEXT
Most Answers	His speech was out of context

4.5 Model Performance Evaluation

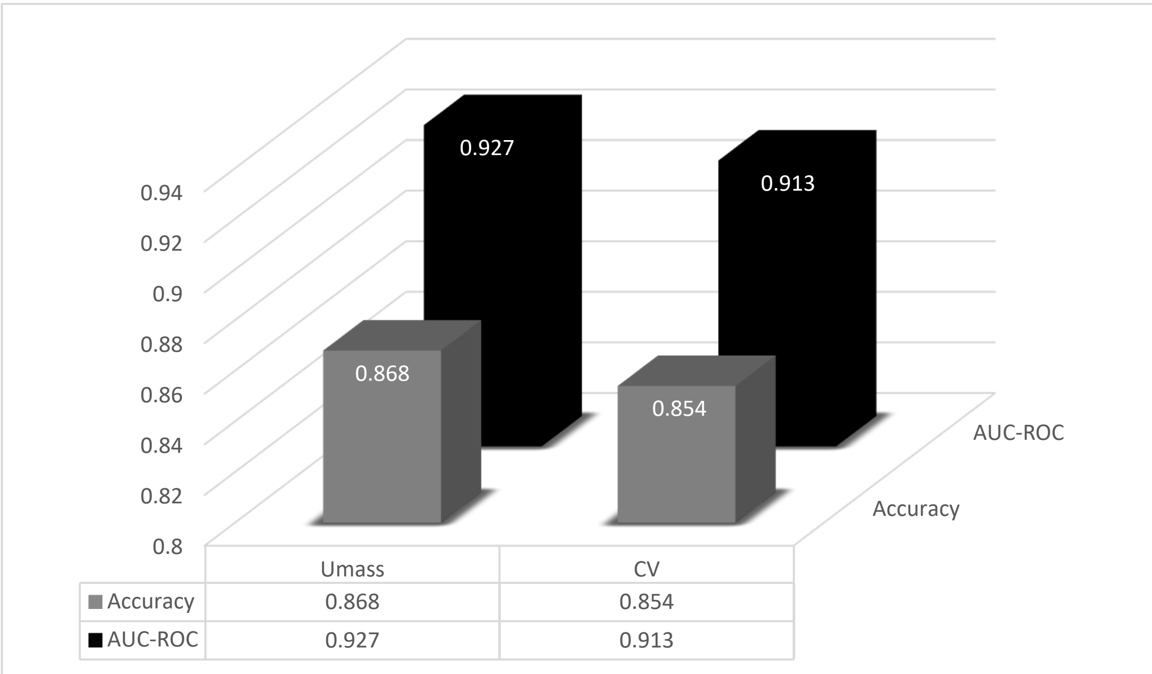
At this stage, features were extracted from the data, represented as feature vectors, and used to train a model. The model's performance was evaluated using test data to identify the most effective approach for predicting sentiments in tweets. To evaluate the effectiveness of our sentiment classification and topic modeling approaches, we compared the performance of traditional machine learning models, deep learning architectures, and BERTopic coherence metrics, as shown in Figure 8.



(a)



(b)



(c)

Figure 8. Model performance comparison: (a) traditional ML, (b) deep learning, (c) BERTopic coherence

`The performance of sentiment classification models was evaluated using accuracy, F1-score, precision, recall, and AUC-ROC. Support Vector Machines (SVM) achieved the highest performance (accuracy: 0.902, F1-score: 0.902, AUC-ROC: 0.961), outperforming Random Forest (accuracy: 0.87), Naive Bayes (accuracy: 0.85), Logistic Regression (accuracy: 0.89), LSTM (accuracy: 0.88), and BERT (accuracy: 0.89). These metrics confirm SVM's suitability for structured text data, while deep learning models excelled in capturing contextual nuances.

5. DISCUSSION

This study provides a comprehensive analysis of Generation Z's sentiment dynamics during X firestorms, using the HBS "Online Connext 2022" event as a case study. By integrating BERTopic modeling with hashtag analysis, we uncover the emotional triggers, thematic clusters, and structural dynamics of coordinated activism, offering a multidimensional perspective on how digital natives respond to perceived brand misconduct. The findings extend existing research on e-WOM, brand transgressions, and online firestorms, while addressing the underexplored role of Generation Z in shaping brand reputations through social media.

5.1 Theoretical Contributions

This study advances marketing, consumer behavior, and data science through several theoretical contributions. First, it enriches the e-WOM literature by emphasizing negative sentiment in driving Generation Z's collective action. Unlike prior studies focusing on positive e-WOM's impact on brand loyalty, our findings highlight how negative criticism, amplified by hashtags, fuels viral outrage. The dominance of negative sentiments (69% of tweets) aligns with brand hate [35], revealing how ethical breaches trigger intense emotional responses that overshadow positive sentiments in crises. This nuanced perspective on e-WOM's dual nature underscores the power of coordinated activism. Second, the study introduces a novel analytical framework combining BERTopic modeling and hashtag analysis, addressing gaps in traditional approaches to social media data. While sentiment analysis and topic modeling have been widely applied, their integration with hashtag analysis to capture both semantic content and structural dynamics is innovative. BERTopic's ability to identify coherent themes (e.g., ideology, leadership, ethics) in short, informal texts like tweets surpasses traditional methods like

LDA, offering greater interpretability and granularity [34-35]. Hashtag analysis complements this by revealing how tags like #HBSONLINECONNEXT serve as digital anchors, organizing fragmented criticisms into unified campaigns. This synergy provides a comprehensive lens for studying coordinated activism, advancing theoretical frameworks for analyzing social media firestorms.

Third, the study contributes to the literature on Generation Z by highlighting their unique behavioral patterns as digital natives. Their heightened sensitivity to ethical breaches and strategic use of hashtags to coordinate activism distinguish them from previous generations. The findings align with research on their role in social movements (e.g., #FridaysForFuture), but extend this to brand contexts, demonstrating how Generation Z leverages social media to demand accountability. The identification of thematic clusters around ideology and ethics underscores their values-driven approach, enriching theories of consumer behavior in the digital age. Finally, the study bridges marketing and data science by applying advanced computational techniques (e.g., SVM, LSTM, BERT) to dissect sentiment and thematic drivers.

The superior performance of SVM (accuracy: 0.902, AUC-ROC: 0.961) compared to deep learning models like LSTM (accuracy: 0.88) and BERT (accuracy: 0.89) suggests that structured text classification remains highly effective for smaller datasets, while deep learning excels with larger, more complex data. This comparative analysis contributes to methodological debates in NLP, providing a benchmark for future studies on social media data.

5.2 Practical Implication

The findings provide actionable strategies for brands navigating social media crises. First, the prevalence of negative sentiments (69% of tweets) highlights the need for proactive crisis management. Real-time monitoring of hashtags like #HBSONLINECONNEXT, used in 29% of tweets, enables early detection of coordinated activism, minimizing reputational damage. By addressing key emotional triggers, such as “unethical behavior” (645 mentions), brands can effectively mitigate negative e-WOM and restore consumer trust. Second, the study emphasizes the importance of transparency and accountability in responding to Generation Z’s ethical concerns. Their sensitivity to ideological and ethical breaches suggests that brands must align their actions with social responsibility. For example, issuing timely apologies or policy changes, as seen in the Starbucks

#BoycottStarbucks case, can de-escalate firestorms. Brands should also engage directly with consumers on platforms like X, using authentic communication to rebuild trust. Third, the thematic clusters identified (e.g., ideology, leadership) provide a roadmap for crafting targeted responses. Brands can address specific consumer grievances, such as perceived ideological bias, by clarifying their values or revising controversial actions. This granular understanding of sentiment dynamics enables brands to tailor their crisis communication strategies, enhancing their effectiveness.

Finally, the comparative performance of machine learning models offers practical guidance for brands leveraging data analytics. SVMs' high accuracy and efficiency make them a cost-effective choice for smaller datasets, enabling brands with limited resources to implement robust sentiment analysis. For larger datasets, deep learning models like BERT can capture nuanced patterns, supporting more sophisticated reputation management strategies. Brands should integrate these tools into their marketing frameworks to monitor consumer sentiment and predict firestorm risks (See Table 7).

Table 7. Practical recommendations for brands managing X firestorms

Strategy	Description	Example/Action
Real-Time Monitoring	Track hashtags and sentiment to detect outrage early.	Use tools to monitor #HBSONLINECONNEXT trends.
Transparency	Issue timely apologies or policy changes to address ethical concerns.	Publicly clarify values or revise controversial actions.
Targeted Communication	Address specific grievances (e.g., ideology, ethics) in responses.	Tailor messages to thematic clusters identified in tweets.
Data Analytics	Use SVM or BERT for sentiment analysis to predict risks.	Implement SVM for cost-effective monitoring of smaller datasets.

Based on the Deployment phase of CRISP-DM, the proposed hybrid framework will be packaged as a Python-based dashboard using Streamlit. In its current conceptual stage (not yet fully designed or implemented), the tool is envisioned to ingest real-time X streams via the academic API, apply the trained SVM classifier (accuracy: 0.902), and visualize BERTopic clusters and hashtag networks in an interactive interface. Brands could upload custom keyword lists, monitor emerging firestorms, and receive automated response templates tailored to detected themes (ideology, ethics, leadership). Once developed, the dashboard will be made open-source on GitHub, enabling replication and adaptation across industries.

Beyond marketing, this framework has broader implications across management, commerce, and computer science. In management, it enables firms to monitor employee and consumer sentiment in real time. In e-commerce, it supports automated reputation management through machine learning-based sentiment tracking. From an NLP perspective, the integration of BERTopic and SVM demonstrates how hybrid models can extract actionable insights from unstructured data. In computer science, the study contributes to scalable architectures for processing high-volume social data.

5.3 Limitations and Future Research

Despite its contributions, this study has notable limitations that guide future research. Primarily, its focus on X excludes sentiment dynamics on platforms like Instagram or TikTok, where Generation Z is highly active, potentially limiting the findings' generalizability. Cross-platform interactions may reveal unique activism patterns. Additionally, the study's reliance on the HBS "Online Connext 2022" case may not capture the diversity of brand misconduct scenarios, as cultural or industry-specific factors could shape sentiments differently. Third, the dataset (3,898 tweets) is relatively small compared to global firestorms, which may affect the robustness of deep learning models like LSTM and BERT, which perform better with larger datasets. The manual labeling of 10% of tweets for sentiment analysis introduces potential bias, despite efforts to ensure balance. Fourth, the study does not account for cultural variations in Generation Z's responses, which could differ across regions or demographics. Finally, the reliance on English-language tweets excludes non-English perspectives, limiting the global applicability of the findings. Future research can address these limitations and extend the study's contributions. First, cross-platform analyses incorporating Instagram, TikTok, and Reddit could provide a holistic view of Generation Z's activism, capturing platform-specific nuances. For instance, TikTok's video-based format may amplify emotional expressions differently than X's text-based structure. Second, expanding the scope to include diverse case studies (e.g., fashion, technology, or nonprofit sectors) would enhance the generalizability of findings, revealing how industry context shapes firestorm dynamics. Third, larger datasets could improve the performance of deep learning models, enabling more accurate sentiment classification and topic modeling. Automated labeling techniques, such as active learning, could reduce manual bias and scale sentiment analysis. Fourth, cross-cultural studies examining Generation Z's responses in different regions (e.g., Asia, Europe) would uncover variations in ethical sensitivities and activism strategies, enriching global consumer behavior theories. Fifth, longitudinal studies tracking firestorm lifecycles over extended periods could reveal how sentiments evolve and whether brands recover from reputational damage. Finally, integrating qualitative methods, such as interviews with Generation Z activists, could provide deeper insights into their motivations and decision-making processes, complementing the quantitative findings of this study.

6. CONCLUSION

Generation Z's fusion of moral clarity and digital mastery has permanently altered the rules of brand survival. The 2022 HBS OnlineConnext firestorm, ignited by a single keynote perceived as ideological overreach and sustained by the relentless drumbeat of #HBSONLINECONNEXT, demonstrated how swiftly ethical missteps can spiral into reputational collapse. From a dataset of 3,898 tweets, 69% radiated outrage, with SVM classification confirming the signal at 90.2% accuracy. The evidence is unequivocal: Gen Z does not tolerate perceived betrayal. They do not complain in isolation; they mobilize, amplify, and demand systemic change. This is not fleeting backlash; it is a new social contract. Brands now operate under constant, hashtag-powered scrutiny where a single misaligned message can trigger coordinated accountability. The path forward demands preemptive vigilance through real-time sentiment tracking, unfiltered honesty that acknowledges fault without deflection, and responses precisely calibrated to the triad of ideology, ethics, and leadership concerns that dominate Gen Z discourse. Those who treat firestorms as data-rich wake-up calls, leveraging scalable tools like the open-source Streamlit dashboard, will turn crises into credibility. They will not merely survive scrutiny; they will earn loyalty by proving alignment with the values their youngest consumers live by. In the Gen Z era, silence is complicity, authenticity is the only firewall, and proactive ethical leadership is no longer optional; it is the price of relevance.

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