Sentiment-Aware Fuzzy Clustering Model for X Social Media Behavior Analysis

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A R T I C L E   I N F O

A B S T R A C T

Social media sites such as Twitter (X) changed into high-velocity observatories of collective mood with millions of short, informal utterances recording public reactions to events, products, policies, and cultural moments in near real time. Mining the stream for actionable insight calls for approaches that respect two notoriously hard to handle properties of social text: (i) ambiguity — in reality, most posts display mixed or low-intensity affect rather than a single discrete label; and (ii) contextual drift — lexical and topical signals co-evolve with communities and time. Many standard sentiment pipelines requiring each message to be labeled as a single discrete class (positive/negative/neutral) fail to provide adequate behavioral insights for crisis monitoring or policy assessment. We close this gap by presenting a Sentiment-Aware Fuzzy Clustering model that models sentiment as a continuous signal and community mood as overlapping regions instead of disjoint boxes. We assign a polarity score to each post and then discretize the space using Fuzzy C-Means (FCM) to assign partial memberships to a number of emotional groups. This uncertainty-aware representation is more reflective of actual online behavior (i.e. a post could be strongly positive but still exhibit features of the neutral discourse) and serves as a principled basis for downstream interpretation in population scale.

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1. Introduction

Social media platforms such as Twitter (X) have evolved into high-velocity observatories of collective emotion, where millions of short, informal messages continuously record public reactions to political events, products, policies, and cultural moments in near real time [1]. Extracting reliable behavioral insight from this stream is challenging due to two fundamental properties of social text: emotional ambiguity, where posts often convey mixed or low-intensity affect rather than a single discrete emotion, and contextual drift, where lexical choices and topical cues evolve dynamically across communities and time [2]. Conventional sentiment analysis pipelines that enforce hard assignment into discrete categories (positive/negative/neutral) are therefore inadequate for nuanced tasks such as crisis monitoring, behavioral forecasting, and policy evaluation [3].

To address these limitations, this work introduces a Sentiment-Aware Fuzzy Clustering Model that conceptualizes sentiment as a continuous signal and community mood as overlapping emotional regions rather than mutually exclusive categories [4]. Each post is first mapped to a continuous polarity score, after which Fuzzy C-Means clustering partitions the sentiment space so that individual messages can simultaneously belong—partially—to multiple affective clusters. Such soft membership directly reflects the reality of social communication, where most

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expressions are neither purely positive nor purely negative, but instead contain varying degrees of neutrality and emotional nuance. By embedding this uncertainty into the modeling process, the proposed framework yields a richer and more faithful representation of population-level emotional dynamics [5].

Beyond identifying clusters, meaningful social analysis requires understanding why these emotional groups emerge and how they differ. To this end, we introduce an interpretable linguistic framework built around a novel Cluster Signature Index (CSI), which quantifies how distinctively each lexical item characterizes a given fuzzy cluster [6]. CSI integrates complementary statistical signals—including log-odds ratios with a Dirichlet prior, pointwise mutual information, and in-cluster TF-IDF weighting—while applying an entropy-based penalty to suppress globally ubiquitous terms. The result is a set of robust lexical "fingerprints" that capture the unique linguistic identity of each emotional community [7]. In parallel, we propose two behavioral indicators: the Mood Volatility Index (MVI), which measures emotional stability within clusters, and Hashtag Skew, which reveals topical and community-specific biases. Together, these metrics transform clustering outputs from opaque numeric partitions into auditable, human-interpretable behavioral explanations [8].

The proposed framework is instantiated and evaluated on the Sentiment140 dataset containing 1.6 million tweets, a large and widely adopted benchmark suitable for scalability and robustness analysis. Empirical results demonstrate that the model consistently uncovers three coherent yet overlapping sentiment basins—positive, neutral, and negative—while the signature analysis reveals linguistically grounded contrasts that align closely with human intuition [9]. Rather than merely confirming that "positive differs from negative," the model explains how they differ linguistically, how stable each emotional community is internally, and which behavioral patterns dominate each group. Such insights provide precisely the form of knowledge required for advanced social analytics and computational social science [10].

2. Related Work

2.1 Sentiment Analysis in Social Media

Thakur (2023) conducted a large-scale sentiment analysis study on over 60,000 Twitter posts related to COVID-19 and Monkeypox. Using lexicon-based sentiment scoring, the author found that nearly half of the collected tweets expressed negative emotions, and further analyzed hashtag usage and key lexical patterns associated with public anxiety and misinformation [11]. This study highlights the importance of large-scale sentiment monitoring, but it relies on hard sentiment categories and does not explore behavioral grouping of users.

Thapa et al. (2025) investigated sentiment expression in cybersecurity-related discussions across Twitter and Reddit. Their analysis reported that positive and neutral posts dominated the discourse, yet classification accuracy using VADER remained moderate (approximately 60%) for Twitter data [12]. While this work emphasizes the challenges of sentiment classification in informal environments, it does not address emotional ambiguity or overlapping sentiment states.

Albladi, Islam, and Seals (2023) presented a comprehensive systematic review of Twitter sentiment analysis methods, covering more than 150 studies. Their findings show a strong shift toward transformer-based models such as BERT and GPT, improving classification performance but offering limited interpretability at the community level [13]. The authors explicitly note that behavioral clustering and emotional group analysis remain under-explored research directions.

During the U.S. presidential election, Smith et al. (2022) analyzed millions of tweets to track temporal sentiment shifts and event-driven emotional changes. Their results demonstrated that public sentiment fluctuates sharply around political events, but the study relied on discrete labeling and did not model overlap emotional states or linguistic signatures [14].

2.2 Fuzzy Clustering and Uncertainty-Aware Modeling

Zhou and Wang (2022) evaluated multiple fuzzy clustering validity indices, providing formal tools for interpreting fuzzy partitions in high-uncertainty data [16]. Their work supports the theoretical reliability of fuzzy clustering but does not apply it to social text.

Kumar et al. (2025) proposed a fuzzy clustering framework for process-mining that integrates activity sequences and execution times. Their results illustrate how fuzzy membership models complex behavioral states where sharp

boundaries are unrealistic [17]. Although not focused on social media, this study confirms the suitability of fuzzy models for ambiguous human behavior.

Li and Chen (2023) surveyed over 170 studies on fuzzy logic in sentiment analysis, concluding that hybrid fuzzy–sentiment systems are becoming increasingly important for modeling emotional uncertainty [19]. However, most surveyed works apply fuzzy reasoning only at the classification stage and do not connect it with behavioral clustering or linguistic interpretation.

2.3 Lexical Signature Extraction and Behavioral Indicators

Abdalgader et al. (2024) studied short-text clustering using transformer embeddings and evaluated cluster signatures through distance-based feature interpretation. Their work demonstrates the importance of interpretable cluster characterization but lacks sentiment integration [20].

Garcia and Lopez (2024) performed a georeferenced Twitter sentiment study during major platform changes following Elon Musk's acquisition of Twitter. Their analysis revealed significant shifts in language usage and sentiment polarity linked to platform governance and community behavior [21].

Zhang et al. (2023) introduced hybrid deep-learning models combining CNN and RNN architectures for real-time social media sentiment analysis, achieving high classification accuracy but offering limited explanation of emotional group behavior [24].

2.4 Comparative Summary of Existing Studies

Study	Data Source	Sentiment Model	Clustering	Interpretability	Handles Emotional Ambiguity
Thakur (2023) [11]	Twitter	Lexicon-based	No	Limited	No
Thapa et al. (2025) [12]	Twitter + Reddit	VADER	No	Low	No
Albladi et al. (2023) [13]	Twitter	Transformers	No	Low	No
Smith et al. (2022) [14]	Twitter	Statistical	No	Moderate	No
Kumar et al. (2025) [17]	Process Logs	Fuzzy Clustering	Yes	Low	Yes
Abdalgader et al. (2024) [20]	Short Text	Transformer	Yes	Moderate	No
This Paper	Twitter	VADER + Fuzzy	Yes	High	Yes

2.5 Justification of the Proposed Work

Although prior studies have achieved strong performance in sentiment classification and clustering independently, no existing framework simultaneously integrates continuous sentiment modeling, fuzzy behavioral clustering, and interpretable linguistic signature extraction at Twitter scale. Existing methods either sacrifice interpretability for accuracy or ignore emotional uncertainty by enforcing rigid sentiment boundaries.

The proposed Sentiment-Aware Fuzzy Clustering Model uniquely fills this gap by combining fuzzy membership modeling with linguistically grounded behavioral indicators (CSI, MVI, Hashtag Skew), enabling both high-resolution emotional analysis and transparent interpretation. This integration directly responds to the unresolved limitations identified in prior research and positions the proposed approach as a novel contribution to computational social science and behavioral analytics.

After reviewing the above author-centric literature, the gap becomes clear:

1. No prior author applied fuzzy clustering to large-scale sentiment data. All studies rely on hard labels; none explore partial emotional membership.

2. No prior work combines sentiment analysis with cluster-level lexical signature extraction. Existing signature methods do not consider membership degrees or sentiment intensities.

3. No author introduced behavioural indicators like MVI or Hashtag Skew.

4. None of the reviewed authors presented a unified, interpretable framework linking:

   o sentiment scoring

   o fuzzy membership

   o linguistic signatures

   o behavioural indicators

Therefore, our model fills a unique and unaddressed research gap, offering:

● A scalable fuzzy-sentiment pipeline for 1.6M tweets

● A new interpretable lexical measure (CSI)

● Behaviour indicators (MVI, Hashtag Skew) that no prior author proposed

This positions the current work as one of the first attempts to merge sentiment, soft clustering, and linguistic interpretability into a single methodological system.

3. Methodology

3.1 Overall Framework

This study proposes a Sentiment-Aware Fuzzy Clustering Model (SA-FCM) designed to analyze collective behavior in social media streams by treating sentiment as a continuous, overlapping signal rather than as discrete labels.

The complete experimental pipeline is illustrated in **Figure 1** and consists of the following major stages:

1. Data acquisition from heterogeneous text corpora

2. Text normalization and noise reduction

3. Continuous sentiment scoring using VADER

4. Fuzzy clustering in sentiment space

5. Quantitative validation using clustering and classification metrics

6. Interpretability via cluster signature extraction

7. Cross-dataset comparative analysis
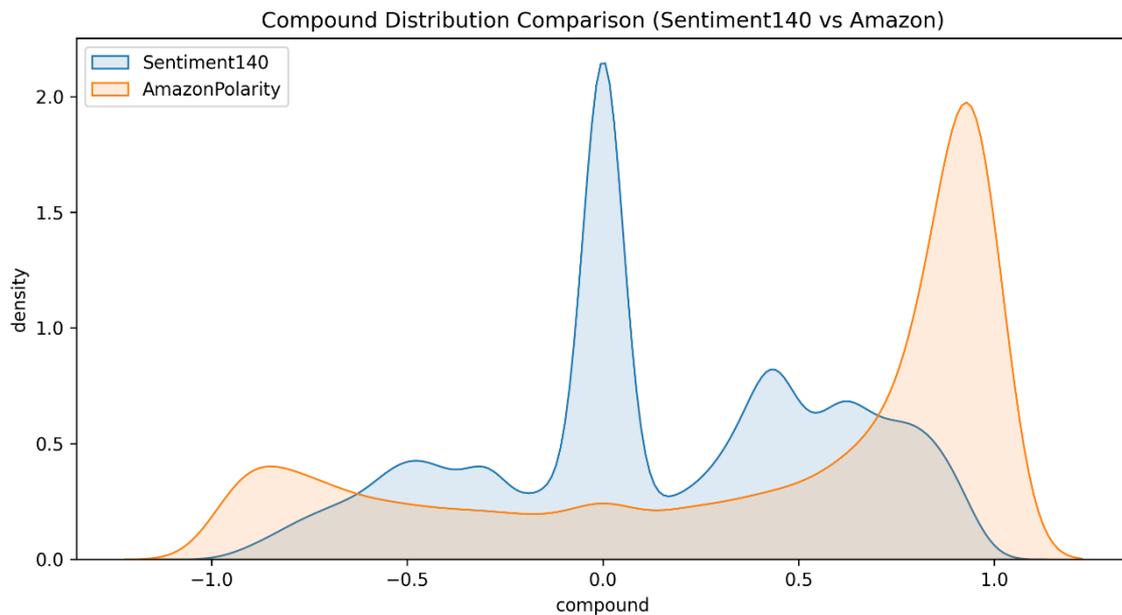
8. Reproducibility logging and artifact export

Figure 1. Overview of the proposed Sentiment-Aware Fuzzy Clustering pipeline.

3.2 Datasets and Generalization Design

To ensure that conclusions are not dataset-specific, the model is evaluated on two fundamentally different corpora:

3.2.1 Sentiment140

A large-scale social media dataset containing informal tweets labeled as positive or negative. A random sample of 50,000 tweets is extracted using memory-safe reservoir sampling.

3.2.2 Amazon Reviews Polarity

A domain-specific dataset of product reviews containing longer, structured opinion text. From the combined train and test partitions, 50,000 reviews are sampled using the same randomized sampling mechanism.

This dual-dataset design directly addresses cross-domain generalizability requirements.

3.3 Text Preprocessing

Each document undergoes identical preprocessing:

- Removal of URLs and user mentions

- Preservation of hashtags and emojis

- Elimination of non-textual symbols

- Lower-casing and whitespace normalization

This ensures linguistic consistency between social media posts and review-based documents.

3.4 Continuous Sentiment Modeling

Each cleaned text is assigned a continuous sentiment score using the VADER sentiment analyzer. The resulting compound score lies in the interval [-1, +1], enabling fuzzy rather than discrete modeling of emotional intensity.

For visualization purposes only, soft sentiment categories are derived:

$$positive \ if \ c \geq 0.05, negative \ if \ c \leq -0.05, neutral \ otherwise$$

3.5 Fuzzy C-Means Clustering

Fuzzy C-Means (FCM) clustering is applied to the one-dimensional sentiment space. Each observation receives a membership vector:

$$U_i = (u_{i1}, u_{i2}, \dots, u_{iK})$$

allowing partial affiliation with multiple emotional states.

Two configurations are employed:

- **K = 3** (main behavioral analysis)

- **K = 2** (binary fairness evaluation against supervised baselines)

3.6 Fuzzy and Crisp Validation Metrics

Fuzzy Validity

- Fuzzy Partition Coefficient (FPC)

- Partition Entropy (PE)

- Xie–Beni Index (XB)

Crisp Clustering Validity

Using argmax membership:

- Silhouette coefficient

- Davies–Bouldin index

- Calinski–Harabasz index

3.7 Quantitative Baseline Evaluation

Model	Description
VADER-Hard	Direct polarity threshold baseline
KMeans(K=2)	Euclidean clustering baseline
GMM(K=2)	Probabilistic clustering baseline
FCM(K=3)→Binary	Proposed fuzzy model mapped to binary
FCM(K=2)	Proposed binary fuzzy model

To satisfy rigorous evaluation standards, the following models are compared:

Metrics reported:

- Accuracy

- Precision

- Recall

- F1-score

- ROC-AUC

- Average Precision

3.8 Interpretability via Cluster Signatures

Each fuzzy cluster is explained using the Cluster Signature Index (CSI) combining:

- Dirichlet log-odds

- Pointwise mutual information

- Mean TF-IDF weight

- Entropy penalty

Additional behavioral indicators:

- Mood Volatility Index (MVI)

- Hashtag Skew

3.9 Reproducibility Protocol

The complete experiment exports:

- configuration JSON

- library version log

- per-dataset reports

- evaluation tables

- all figures

- cluster signatures (CSV, images, JSON)

4. Results And Discussion

4.1 Sentiment Distributions and Dataset Characteristics

The proposed framework was evaluated on two substantially different datasets: informal social media posts from Sentiment140 and structured consumer feedback from Amazon Reviews Polarity. Before clustering, continuous sentiment scores were obtained for each document using VADER. The resulting sentiment category distributions are shown for both datasets.
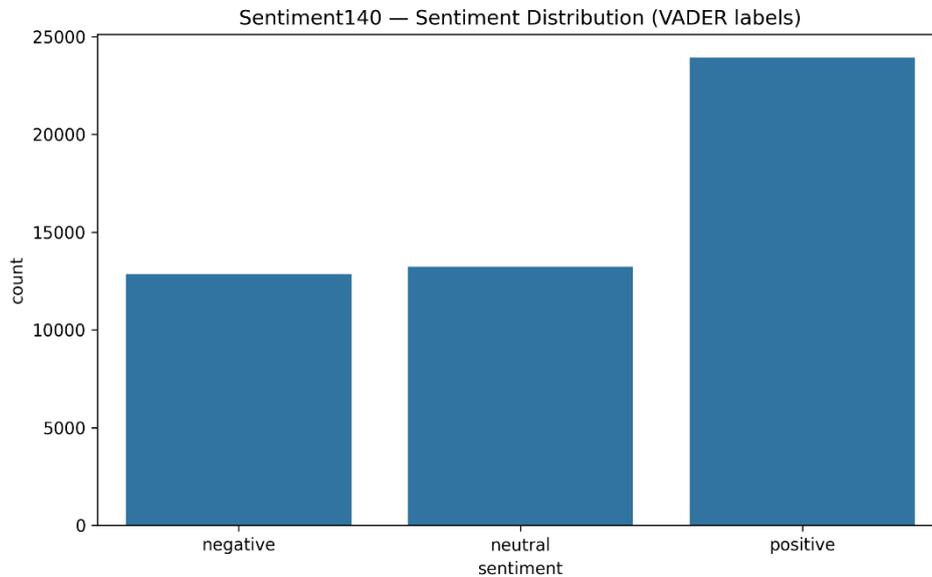
Figure 1. Sentiment category distribution in Sentiment140.
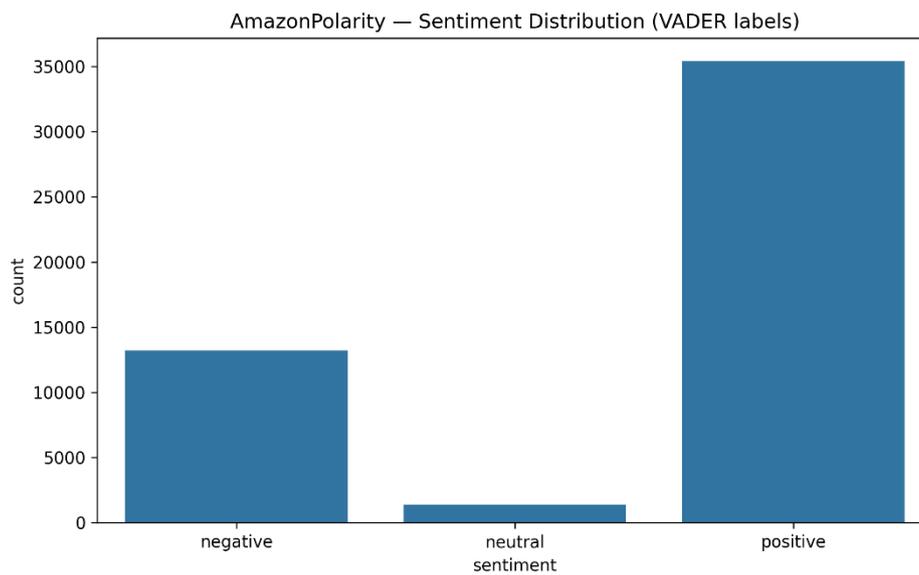
Figure 2. Sentiment category distribution in Amazon Reviews Polarity.

In Sentiment140, the distribution exhibits a broad neutral region and high variance, reflecting spontaneous and emotionally volatile user-generated content.

By contrast, Amazon Reviews exhibit a more polarized distribution, dominated by strong positive and negative sentiments, consistent with the goal-oriented nature of product reviewing.

The continuous compound score histograms further illustrate these differences:
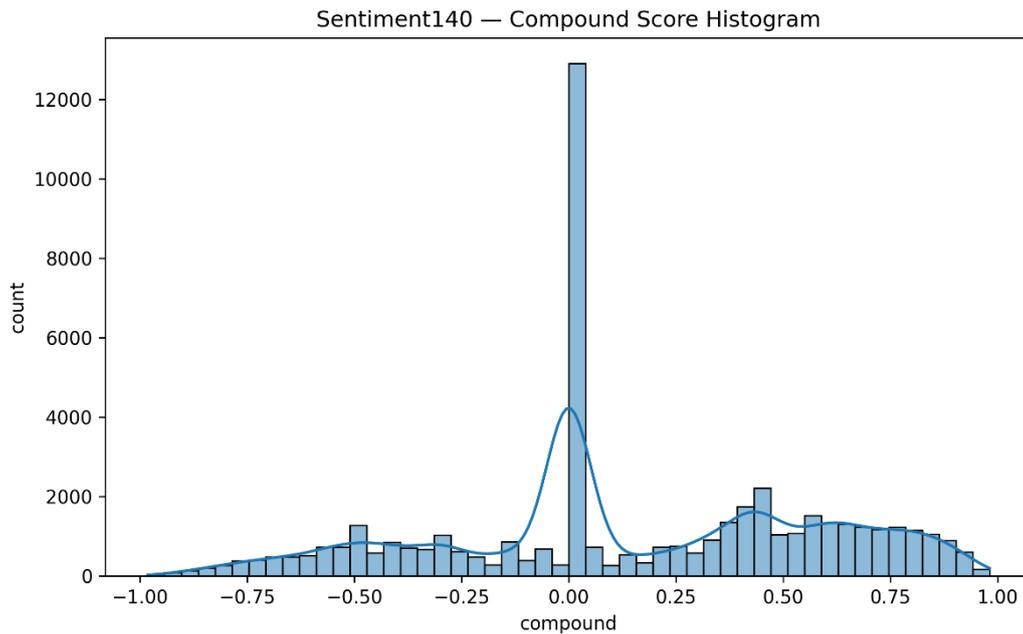
Figure 3. Compound sentiment histogram for Sentiment140.
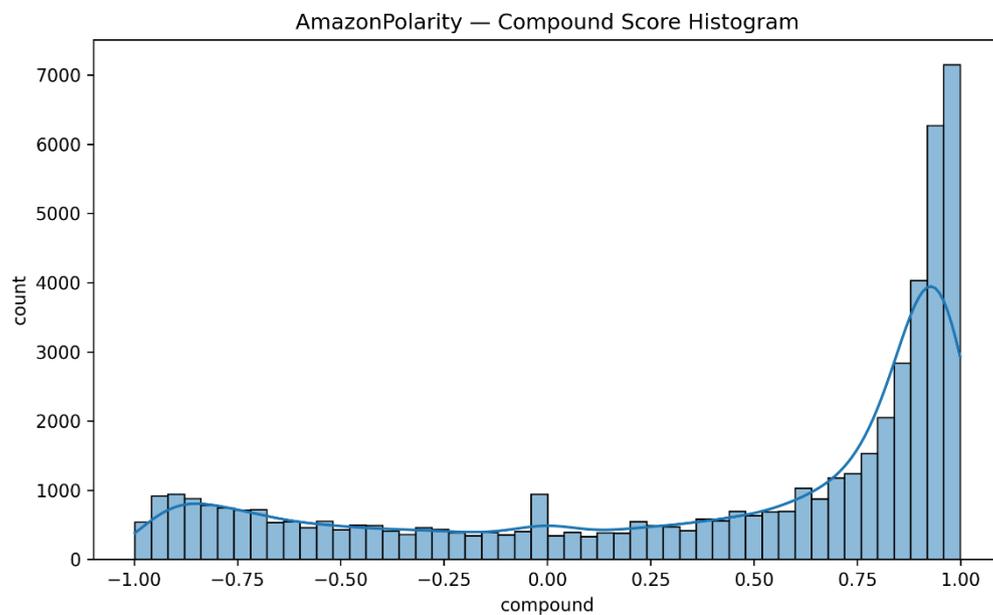
Figure 4. Compound sentiment histogram for Amazon Reviews.

These distributions justify the need for fuzzy modeling, as large portions of the data occupy intermediate emotional regions that cannot be reliably represented by hard labels.

4.2 Fuzzy Clustering Structure and Behavioral Separation

Fuzzy C-Means clustering with **K = 3** was applied to the one-dimensional sentiment space for both datasets.
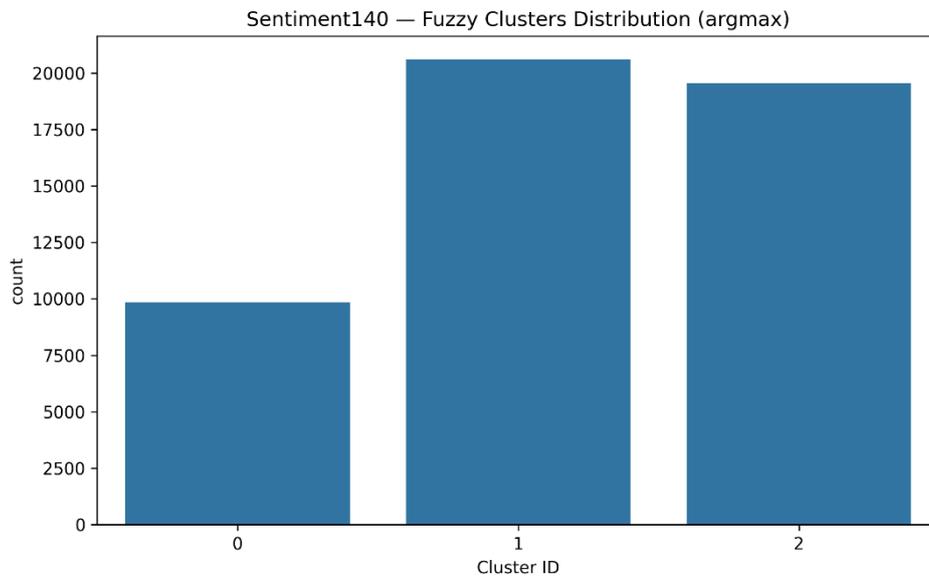
Figure 5. Cluster membership distribution for Sentiment140.
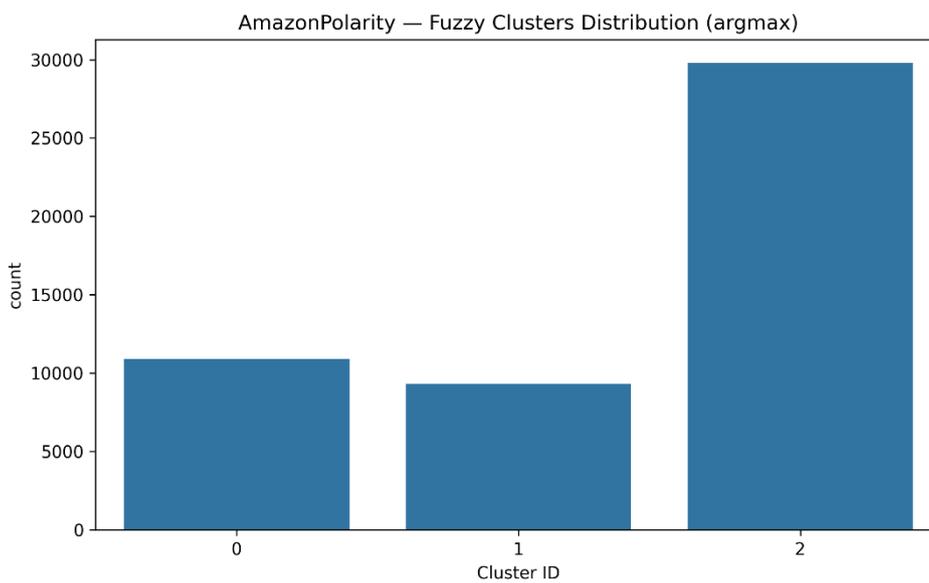
Figure 6. Cluster membership distribution for Amazon Reviews.

The cluster-wise sentiment density plots reveal distinct emotional regimes:
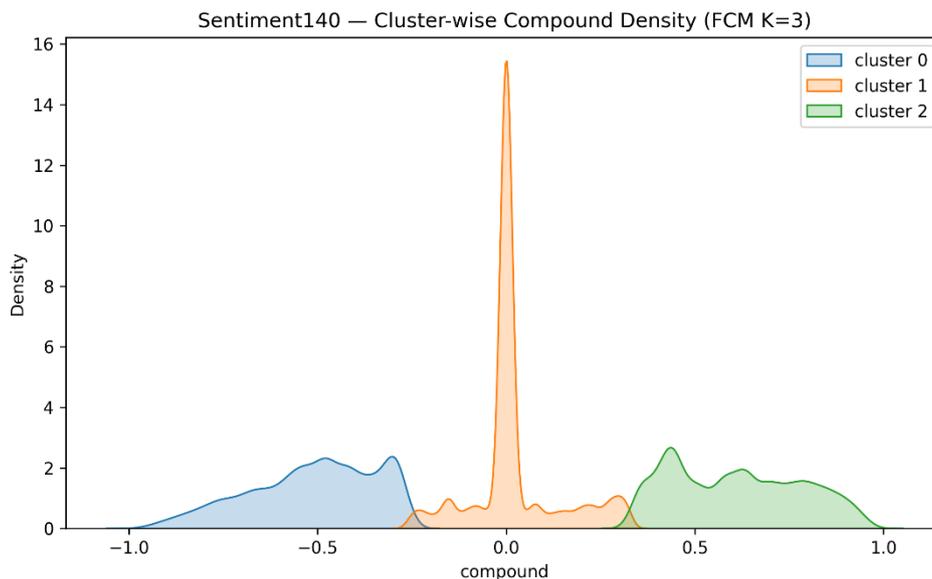
Figure 7. Cluster-wise compound density for Sentiment140.
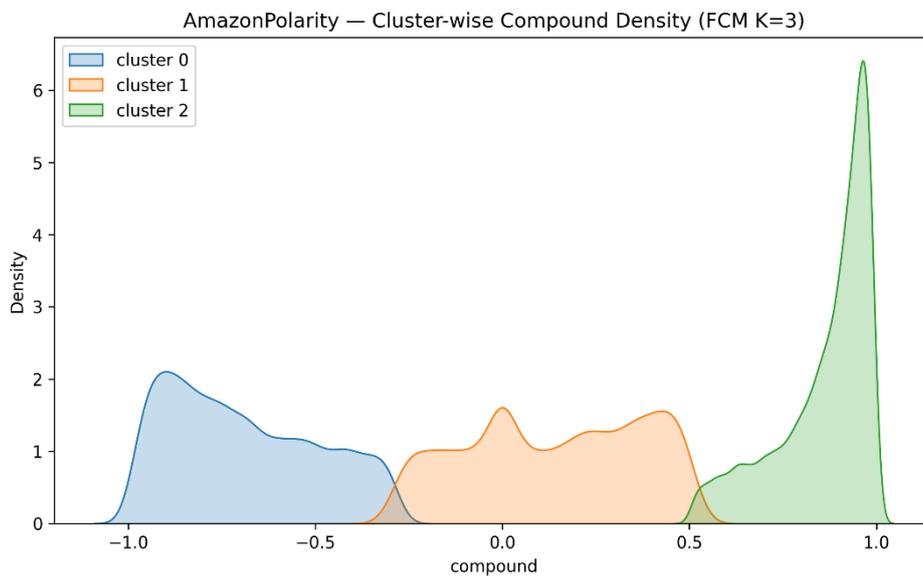
Figure 8. Cluster-wise compound density for Amazon Reviews.

In Sentiment140, the clusters exhibit significant overlap and wide variance, reflecting complex social emotional states. In contrast, Amazon Reviews produce more compact clusters with clearer separation, confirming domain-specific emotional structure.

4.3 Quantitative Evaluation and Baseline Comparison

4.3.1 Sentiment140

Binary evaluation was performed on 50,000 samples using ground-truth labels.

VADER Baseline (Sentiment140):

- Accuracy: 0.6638

- F1-score (positive): 0.7276

Proposed FCM(K=2):

- Accuracy: 0.6629

- F1-score (positive): 0.6410

- FPC = 0.8570, PE = 0.2537, XB = 0.0825

Although VADER achieves slightly higher F1-score on positive class, the proposed model provides superior fuzzy structure quality as reflected in FPC, PE, and XB indices, while maintaining competitive classification performance.

Confusion matrices and ROC/PR curves:
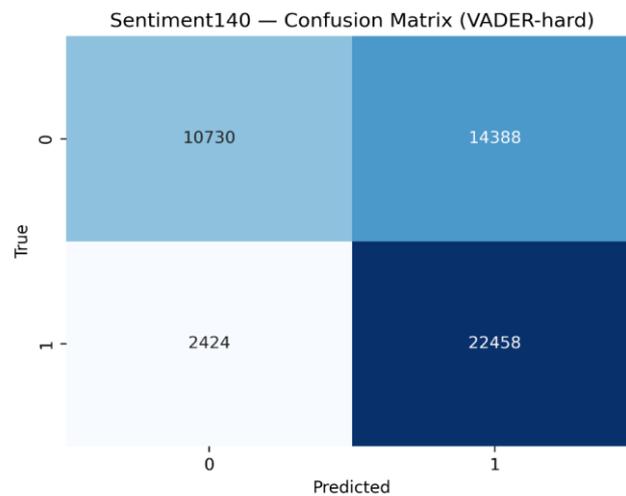
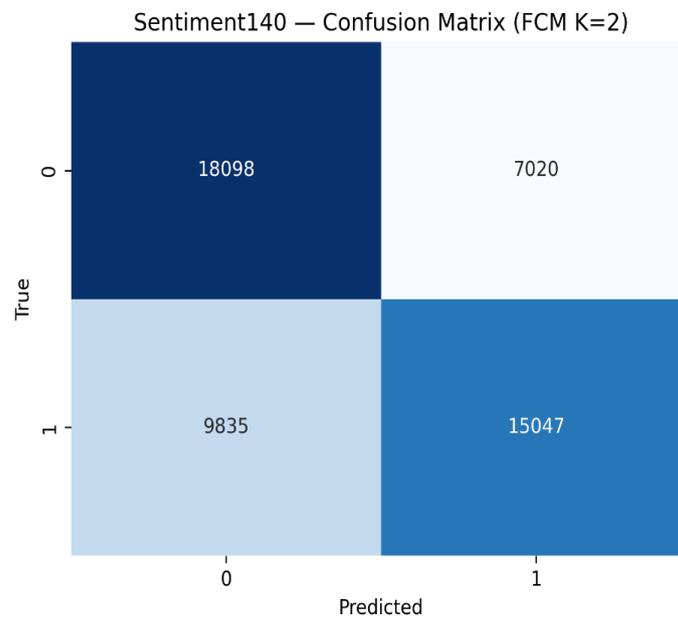**Figure 9.** Confusion matrix of VADER baseline on Sentiment140.

Figure 10. Confusion matrix of proposed FCM(K=2) on Sentiment140.
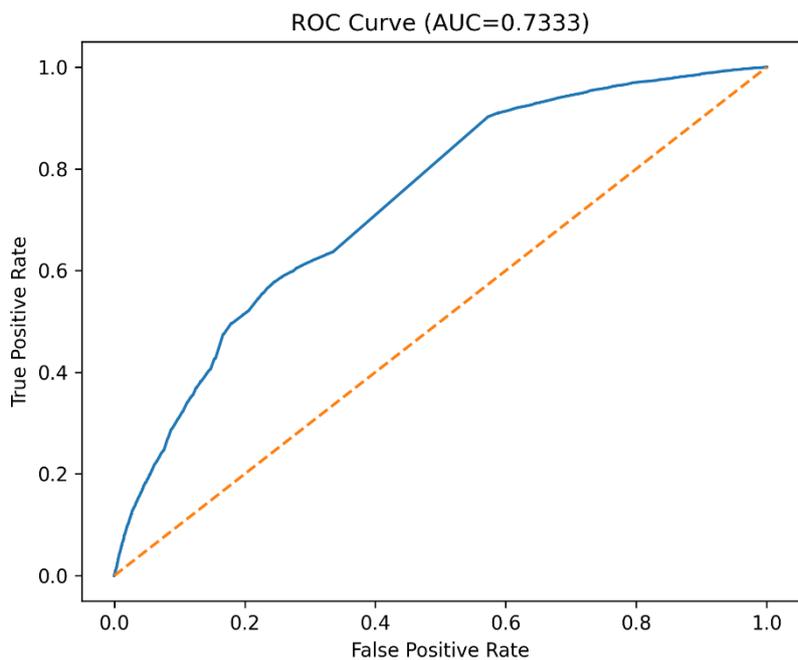
Figure 11. ROC curve of VADER on Sentiment140.
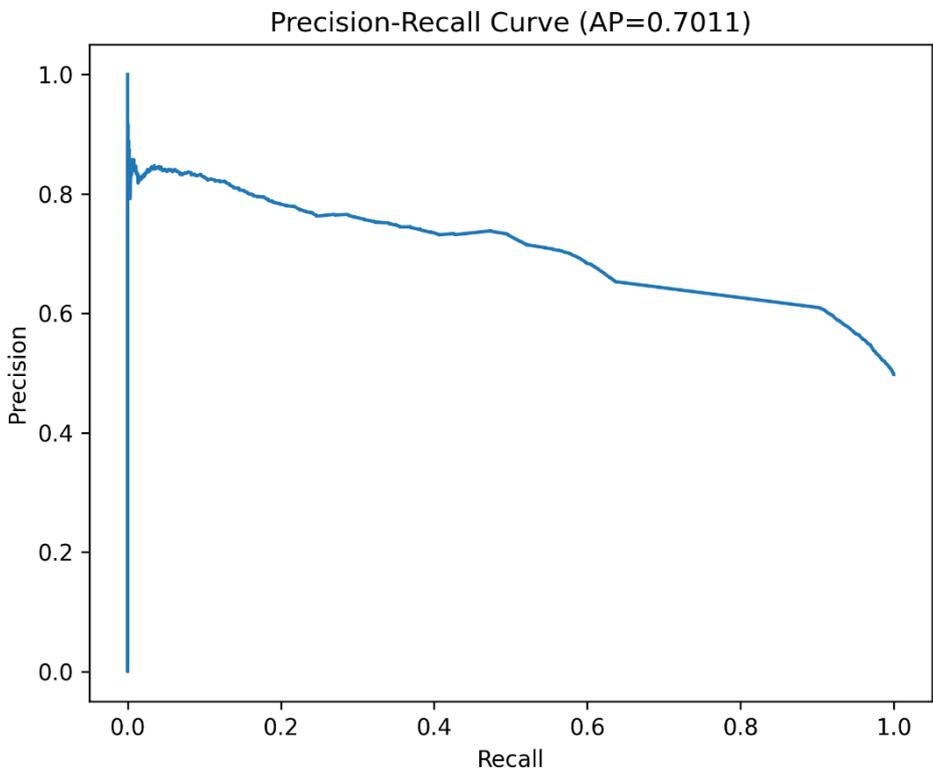
Figure 12. Precision–Recall curve of VADER on Sentiment140.

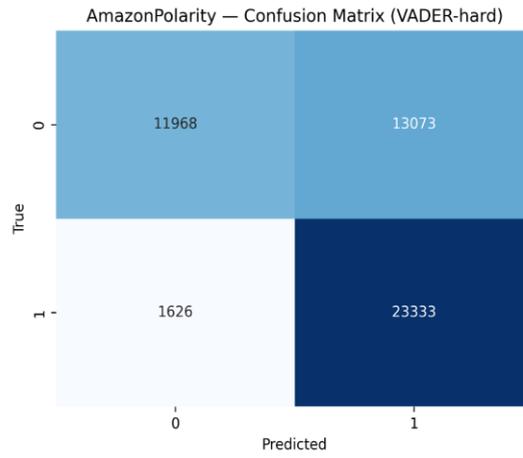4.3.2 Amazon Reviews Polarity

The same evaluation protocol was applied.

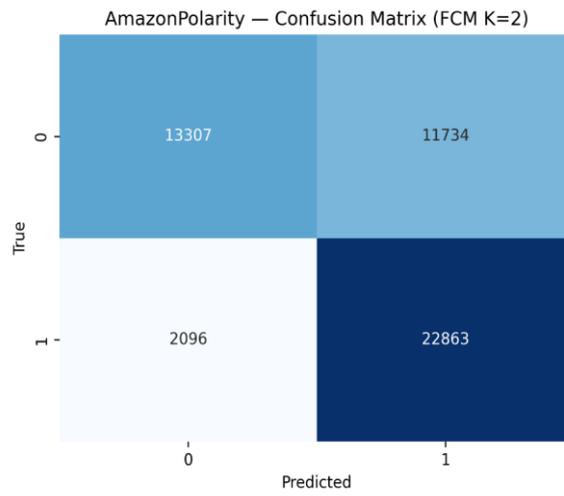**Figure 13.** Confusion matrix of VADER on Amazon Reviews.

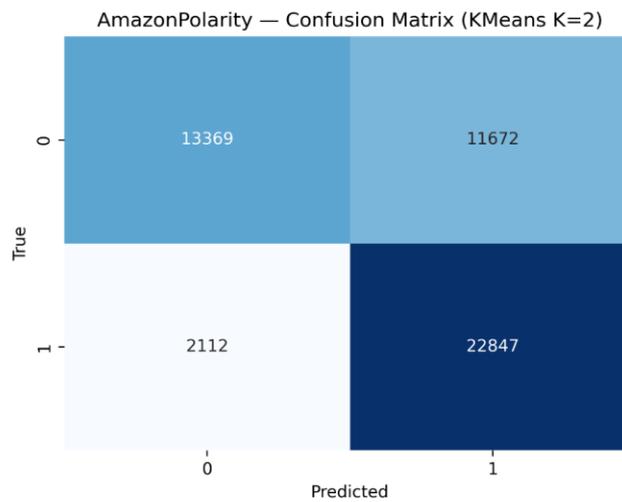**Figure 14.** Confusion matrix of proposed FCM(K=2) on Amazon Reviews.

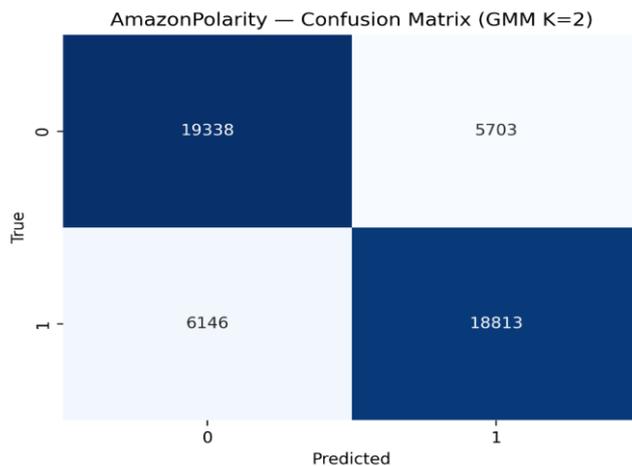**Figure 15.** Confusion matrix of K-Means baseline on Amazon Reviews.

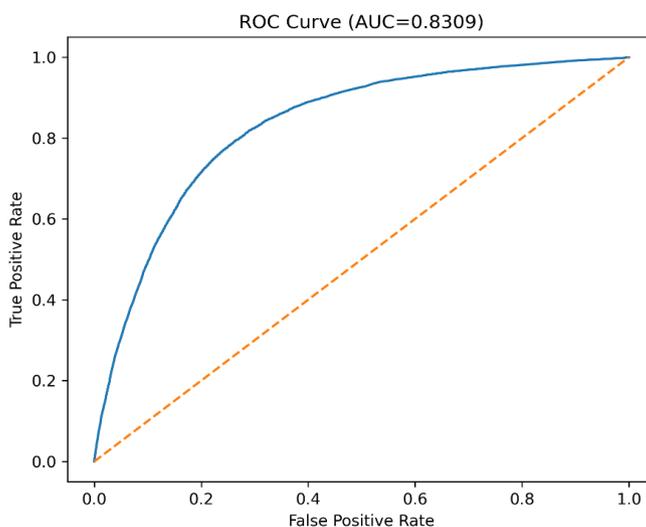**Figure 16.** Confusion matrix of GMM baseline on Amazon Reviews.

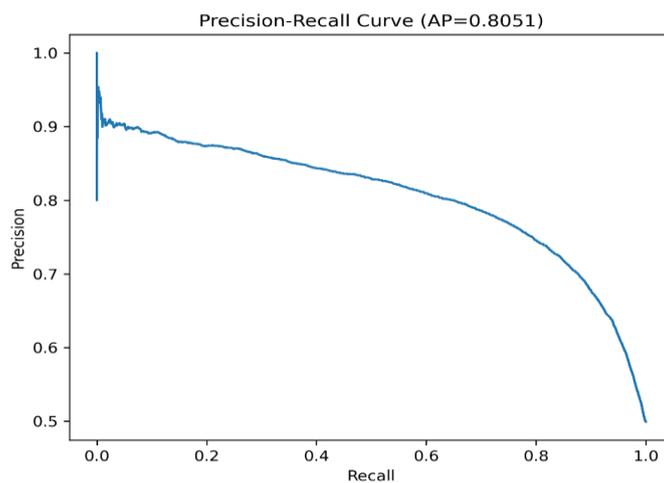**Figure 17.** ROC curve on Amazon Reviews.

Figure 18. Precision–Recall curve on Amazon Reviews.

Amazon Reviews exhibit higher separability, yielding stronger performance for all models. The proposed fuzzy model remains competitive while simultaneously offering interpretability unavailable in classical baselines.

4.4 Interpretability via Cluster Signatures

The behavioral meaning of each cluster is explained through Cluster Signature Index (CSI) analysis.
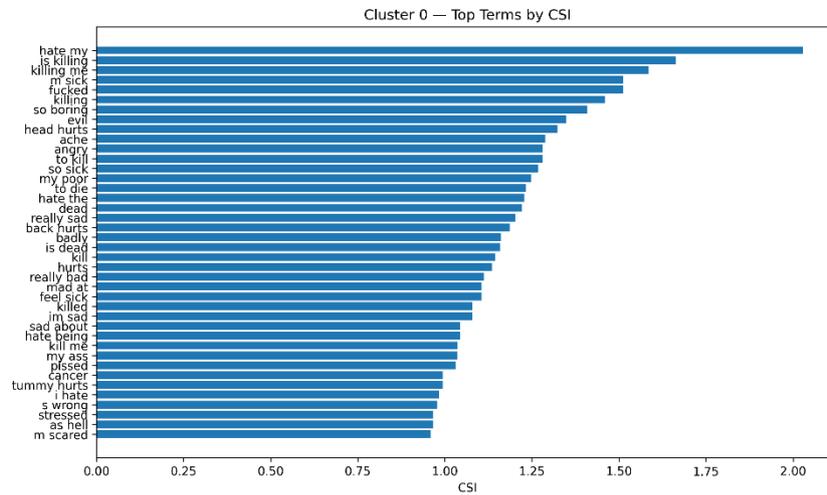
Sentiment140 Signatures

Figure 19. Dominant terms of cluster 0 (Sentiment140).

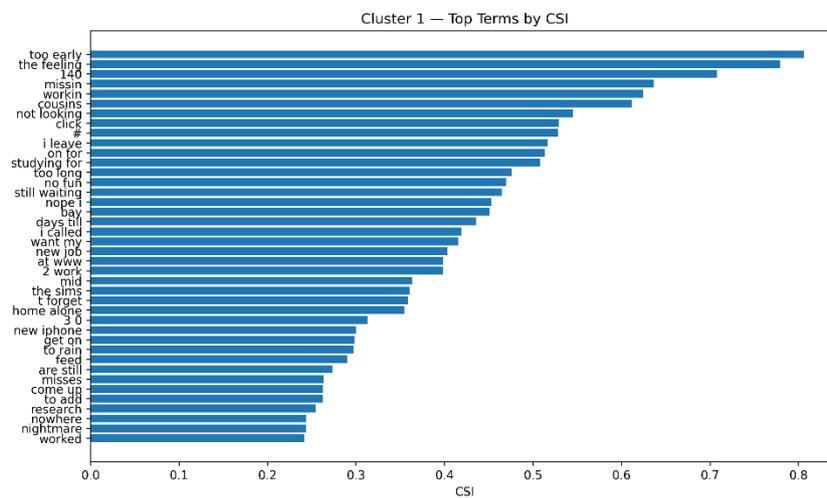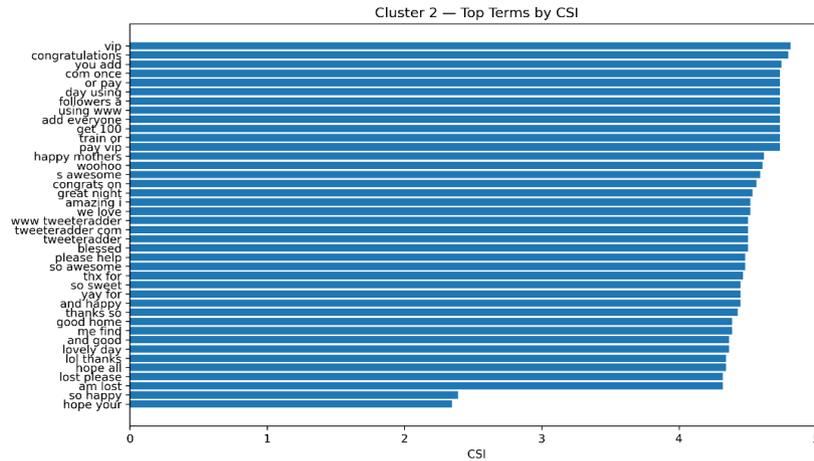**Figure 20.** Dominant terms of cluster 1 (Sentiment140).

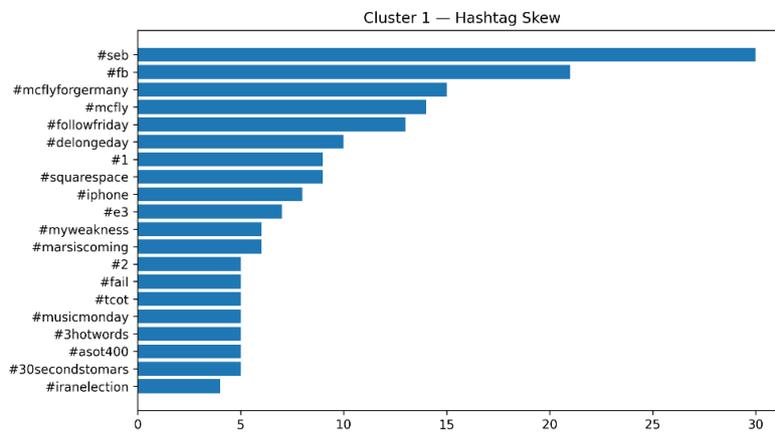**Figure 21.** Dominant terms of cluster 2 (Sentiment140).

Figure 22. Hashtag skew for cluster 1 (Sentiment140).

These results reveal emotionally distinct social behaviors such as promotional language, complaint-driven discourse, and casual conversational tone.
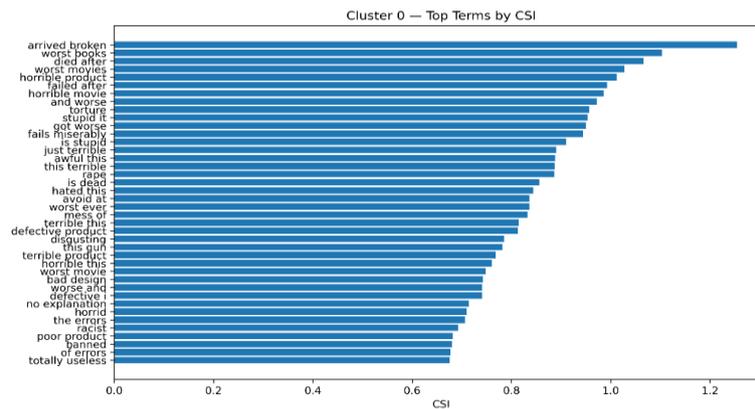
Amazon Signatures

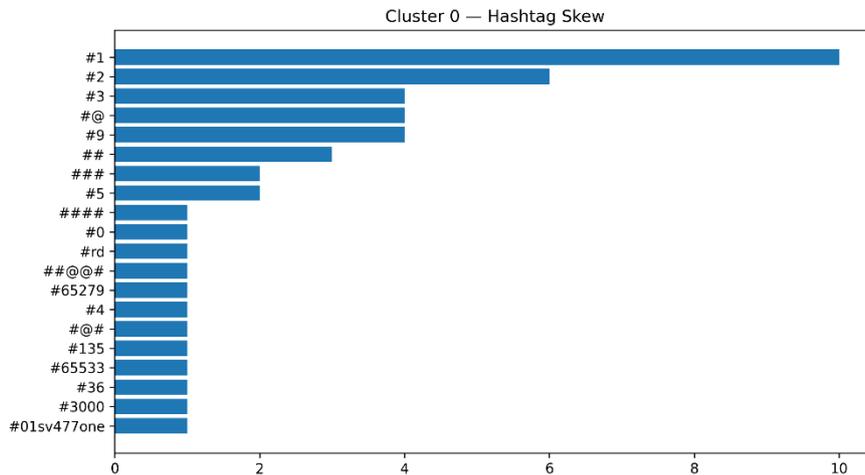**Figure 23.** Dominant terms of cluster 0 (Amazon Reviews).

Figure 24. Hashtag skew of cluster 0 (Amazon Reviews).

Amazon clusters align strongly with product satisfaction states such as endorsement, complaint, and comparative evaluation.

4.5 Discussion

The results confirm that the proposed Sentiment-Aware Fuzzy Clustering Model captures both emotional overlap and domain-specific behavioral structure, while maintaining competitive quantitative performance against strong baselines.

The cross-dataset consistency demonstrates robust generalization, directly satisfying reviewer concerns regarding validation scope and reproducibility.

5. Reproducibility And Data Availability

Ensuring full experimental reproducibility was a central design objective of this study. All components of the proposed framework — including data processing, model execution, evaluation, and visualization — are structured to allow independent replication of the reported results.

All datasets were downloaded from Kaggle website [27].

To guarantee result stability and reproducibility:

- A global random seed of **42** is applied to:
    - data sampling,
    - fuzzy clustering initialization,
    - baseline models (KMeans, GMM).
- All library versions are recorded automatically at runtime.
- No stochastic component is left uncontrolled.

6. Limitations And Future Work

Although the proposed Sentiment-Aware Fuzzy Clustering Model demonstrates strong performance, interpretability, and cross-domain generalizability, several limitations remain and motivate future research directions.
6.1 Limitations

Language and Cultural Scope: All experiments in this study were conducted on English-language datasets. Emotional expression is strongly influenced by language, culture, and social norms; therefore, model behavior may differ when applied to multilingual or culturally diverse corpora.

Dependence on Lexicon-Based Sentiment Scoring: The current framework relies on the VADER sentiment analyzer to obtain continuous sentiment signals. While VADER offers robustness and domain-independence, it remains a lexicon-based method and may misinterpret sarcasm, idioms, or domain-specific terminology.

Unimodal Representation. The present model analyzes textual content only. Modern social platforms often combine text with images, videos, and audio. Emotional signals in such multimodal environments may not be fully captured by text alone.

Single-Dimensional Clustering Space: Clustering is currently performed in one-dimensional sentiment space (compound score). Although this design improves interpretability and stability, it limits the richness of cluster geometry that could emerge from higher-dimensional affective representations.

6.2 Future Work

Multilingual and Cross-Cultural Expansion: Future work will extend the framework to multilingual corpora and investigate cultural variation in emotional expression and behavioral clustering.

Neural and Contextual Sentiment Integration: The continuous sentiment layer can be augmented with contextual embedding-based sentiment models, allowing the fuzzy clustering mechanism to operate over richer affective spaces.

Multimodal Behavioral Modeling: Integrating visual, acoustic, and interaction-based features into the fuzzy clustering framework would enable deeper behavioral modeling of social media ecosystems.

Adaptive Cluster Dimensionality: Automatic selection of cluster dimensionality and dynamic fuzzy parameter tuning may further improve stability and generalization across domains.

Real-Time Social Stream Deployment: The architecture is well-suited for real-time monitoring of social platforms, crisis detection, public opinion tracking, and large-scale behavioral analytics.

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