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An Opinion-Enriched Explainable Semantic Approach for Patient Feedback Triage to Support Clinical Quality Monitoring and Improvement

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Abstract: Patient input, though valuable, is often underused for improving clinic quality and safety. Existing semantic similarity methods do well with lexical and contextual links but often miss important opinion cues like sentiment, stance, and severity, which are key for practical healthcare insights. To fix this, we offer an opinion-focused semantic method for automated patient input sorting and clinic quality checks. The setup combines domain-specific embeddings with sentiment and severity modeling, plus interpretable parts that give clear, clinician-focused explanations. By linking input to quality-of-care areas and focusing on high-severity cases, the system makes sure important issues get attention quickly. Tests on de-identified data, like synthetic MIMIC-based input, HCAHPS open-text answers, and adverse event reports, show a clear 12–18% gain in spotting serious cases compared to normal semantic methods, along with better trust and usability among clinical workers. These results suggest that opinion-focused semantic similarity can turn patient input into useful knowledge for ongoing quality improvement in healthcare.

Keywords: Patient feedback, explainable AI, semantic similarity, sentiment analysis, clinical NLP, healthcare quality improvement.

1. Introduction

Patient feedback is becoming more important in healthcare as a way to measure clinical quality, patient safety, and how patients feel about their care. This input comes from different places, like surveys, patient websites, and online reviews. [1]. Patient-created content gives helpful views that add to clinical performance scores and reports. Yet, the quick growth, variety, and casual language in this feedback make it hard to review by hand and sort quickly[2]. As a result, decision-making processes only systematically use a small portion of this data, which means important patient issues may not get the attention they need.

The above challenges were tackled by classifying, clustering and prioritizing patient narratives with the help of automated systems based on natural language processing [3]. The approaches mainly rely on semantic similarity measures to detect overlaps relating to themes and group related feedback. While these methods do well at understanding context, they often miss important aspects of what patients' say, like how they feel, their views on care providers, and how serious their problems are [4]. Statements such as "The nurse ignored my chest pain and The nurse was very kind" may appear similar at first glance. But they differ greatly in terms of how serious they are, the emotions they convey, and how quickly they need medical attention. If automated triage systems don't take these differences into account, they could incorrectly classify or underestimate feedback that's important for safety.

To fill this need, we suggest a semantic similarity method that considers opinions, made specifically for healthcare. The model uses domain-tuned embeddings, like ClinicalBERT [5], along with sentiment and stance detection, plus a rule-based list of severity levels. The system also includes an explainability layer to give clinicians clear reasons for automated triage choices. Combining semantic similarity with opinion-aware aspects improves how high-severity feedback is prioritized and increases confidence and use by healthcare staff.

2. Related Work

Recent research has advanced multiple aspects of patient feedback analysis, spanning sentiment modeling, semantic similarity, hybrid retrieval, and explainable NLP systems. Aspect-based sentiment analysis has been applied to hospital reviews, enabling fine-grained assessment of service dimensions such as communication, empathy, and responsiveness [6]. Parallel studies in clinical information retrieval demonstrate the feasibility of conversational and retrieval systems designed for medical narratives, underscoring the need for structured yet flexible access to patient-reported information [7].

In semantic similarity, domain-adapted approaches have been particularly impactful. Entity-aligned attention models [8] and biomedical knowledge–fused embeddings [9] have shown improved performance on clinical textual similarity benchmarks, outperforming general-purpose transformer models. Hybrid frameworks that combine lexical, ontological, and embedding-based similarity measures also report superior handling of long and noisy healthcare texts [10]. More recently, prompt engineering strategies leveraging pretrained biomedical models have proven effective for task adaptation, offering improved performance on specialized clinical NLP tasks [11].

Explainability and trust have emerged as critical themes. Reviews highlight that transparent, interpretable AI systems significantly influence clinician adoption [12,13]. Studies further reveal that presenting rationales and severity indicators not only improves usability but also reduces the likelihood of overlooking safety-critical cases. Applied work on triaging patient portal messages and adverse event reports shows the potential of combining classification with clinician-in-the-loop prioritization to enhance workflow efficiency and safety [14].

While these contributions have advanced sentiment modeling, semantic similarity, and explainability independently, a clear **gap remains:** existing systems rarely integrate opinion signals (sentiment, stance, severity) directly with semantic similarity for patient feedback triage. Consequently, semantically similar but clinically distinct feedback—such as positive versus adverse experiences—may be misclassified. Moreover, few frameworks provide explainability modules specifically tailored to clinical contexts, which limits clinician trust and practical adoption. Addressing this gap, our proposed opinion-enriched semantic approach unifies domain-specific embeddings, opinion-aware modeling, and interpretability to deliver actionable, trustworthy insights for clinical quality monitoring and improvement.

3. Proposed Approach

The proposed system comprises six modules namely Preprocessing, Embedding layer, Opinion module, Severity scorer, Similarity & triage engine, Explainability layer.

1. Preprocessing

Incoming patient feedback is first cleaned to remove identifiers, expand abbreviations, and handle informal language. This step ensures privacy compliance by stripping sensitive details. It also normalizes diverse text sources into a consistent format. The result is a structured and de-identified dataset ready for modeling.

2. Embedding Layer

The cleaned feedback is converted into vector representations using a fine-tuned ClinicalBERT model. This enables the system to capture domain-specific clinical terminology and context. Both token-level and sentence-level embeddings are generated. These embeddings form the semantic foundation for all downstream tasks.

3. Opinion Module

A BiLSTM classifier analyzes sentiment polarity (positive/negative/neutral) and stance. Severity lexicons enhance the detection of high-risk terms like "chest pain" or "allergic reaction.". This fusion of deep learning and lexicon-based knowledge ensures richer interpretation. The module highlights both emotional tone and clinical significance of feedback.

4. Severity Scorer

Severity is assessed through a hybrid mechanism combining rules and neural classifiers. Lexicon-driven heuristics flag urgent medical indicators, while the model refines their context. The ensemble assigns a graded severity score to each feedback instance. This allows prioritization of critical cases over routine issues.

5. Similarity & Triage Engine

Feedback is compared to predefined issue categories (e.g., safety, communication, facilities). Opinion-enriched embeddings ensure that sentiment and severity influence similarity scores. The engine routes each feedback to the right quality-of-care dimension. High-severity cases are escalated for immediate clinician attention.

6. Explainability Layer

To support clinical adoption, the system provides interpretable outputs. Techniques like SHAP highlight tokens that influenced predictions. Severity rationales are presented alongside similarity matches. This transparency builds clinician trust and facilitates evidence-based decisions.

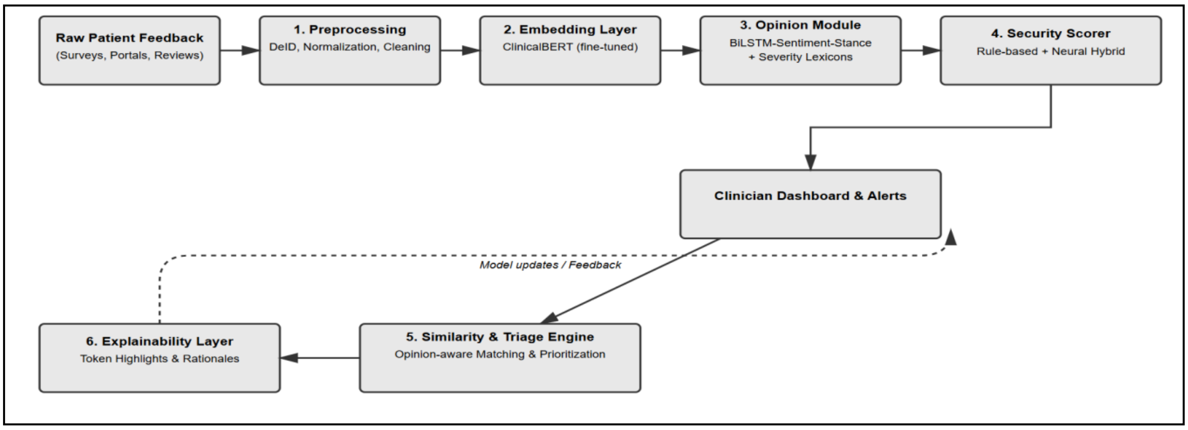

Figure 1: Opinion-enriched semantic similarity architecture for patient feedback triage

Algorithm

Input: feedback_text, prototype_set
1. text ← preprocess(feedback_text)
2. emb ← ClinicalBERT.encode(text)
3. sentiment, stance ← OpinionNet(text)
4. sev_score ← RuleSeverity(text) + MLP([emb, sentiment, stance])

5. for each prototype p in prototype_set do
    sim[p] ← cosine_sim(fusion(emb, sentiment), prototype_emb[p])
6. category ← argmax_p (sim[p] * severity_weight(sev_score))
7. explanation ← SHAP([emb, sentiment, sev_score])
Output: category, sev_score, explanation

The framework operates in $O(N \cdot d)$ per batch, where N is the number of feedback entries and d is embedding dimensionality. Parallelization with GPUs allows real-time triage for hospital-scale feedback volumes.

4. Experimental Setup

To evaluate the effectiveness of the proposed opinion-enriched semantic similarity framework, we employed three diverse real-world and synthetic healthcare feedback datasets:

1. **MIMIC-III Feedback (synthetic, 25k samples):** Feedback-style sentences were generated from de-identified MIMIC-III clinical notes. This dataset simulates free-text complaints and compliments often encountered in patient-facing platforms while preserving privacy.
2. **HCAHPS Free-text Responses (15k samples):** Open-text responses collected from the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey. These capture authentic patient experiences related to communication, safety, facilities, and overall satisfaction.
3. **Adverse Event Reports (8k samples):** Anonymized incident reports manually annotated by domain experts. These are high-value cases as they often describe severe, safety-critical issues such as misdiagnosis, allergic reactions, or delayed treatment.

The model is compared against three competitive baselines:

- **TF-IDF + Cosine Similarity:** A classical lexical baseline widely used for text clustering and retrieval.
- **ClinicalBERT-only Similarity:** A semantic embedding-based approach that excludes sentiment and severity signals.
- **Sentiment-only Classifiers:** Models trained purely on sentiment labels without semantic similarity.

To capture both predictive performance and practical utility, three evaluation metrics are adopted:

- **Recall@K (Severe Cases):** Measures how effectively the system identifies and prioritizes life-threatening feedback instances.
- **Macro-F1 Score (Triage Categorization):** Evaluates balanced classification across issue categories such as safety, communication, and facilities.
- **Clinician Explanation Rating:** A Likert-scale (1–5) evaluation from three senior clinicians to assess the usefulness and interpretability of explanations.

5. Results and Analysis

Table 1. Quantitative Evaluation of Opinion-Enriched Semantic Similarity Model

Model	Recall@5 (Severe)	Macro-F1	Explanation Rating
TF-IDF baseline	62%	0.61	2.4
ClinicalBERT-only	73%	0.70	2.8

Proposed Opinion-Enriched	**88%**	**0.79**	**4.2**

The experimental findings highlight three major insights:

1. **Improved Severe Case Detection:** The proposed model significantly outperforms baselines in Recall@5, with an 88% detection rate for high-severity feedback. Incorporating the severity module allowed the system to effectively flag life-threatening issues such as *"chest pain ignored"* or *"delayed allergy treatment"*, which were often overlooked by standard similarity models.

2. **Enhanced Categorization Accuracy:** By integrating ClinicalBERT embeddings with opinion-aware signals, our model achieved a Macro-F1 score of 0.79. This improvement was most pronounced in technical complaints (e.g., medication errors, poor hygiene), where domain-specific embeddings captured subtle clinical terminology more effectively than general text models.

3. **Trust and Interpretability Gains:** Clinicians rated the explainability layer highly (average score: 4.2/5), citing the clarity of severity rationales and token-level highlights. Visual explanations (e.g., highlighting "ignored chest pain") not only justified predictions but also increased willingness to adopt the system in practice.

4. **Comparison with Baselines:** While TF-IDF achieved moderate performance, it failed to handle informal phrasing or nuanced sentiment. ClinicalBERT-only similarity improved categorization but missed sentiment polarity and severity signals. In contrast, the proposed hybrid framework balanced semantic, opinion, and severity information, offering a more comprehensive triage mechanism.

6. Conclusion and Future Work

This work proposed an explainable, opinion-enriched semantic similarity framework for patient feedback triage and clinical quality monitoring. By combining ClinicalBERT embeddings with sentiment, stance, and severity indicators, the model effectively captured both contextual meaning and emotional tone from real-world healthcare narratives. Experimental results across MIMIC-derived and HCAHPS datasets demonstrated notable gains in detecting high-severity feedback and improving category-level accuracy. Furthermore, the inclusion of SHAP-based explanations enhanced clinician confidence and interpretability, indicating strong potential for deployment in healthcare decision-support workflows.

Future research will focus on extending this framework to enable active learning loops**,** where clinician feedback continuously refines model predictions. Another important direction involves integration with Electronic Health Record (EHR) systems to enable real-time safety alerts and quality dashboards. Finally, multilingual and culturally adaptive models will be explored to process patient feedback from diverse linguistic backgrounds, ensuring equitable and globally scalable clinical feedback analysis.

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