Shabda Chitra: Multi-Agentic Framework for Emotion-Conditioned Bengali Poetry Generation

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Abstract

Shabda Chitra is a multi-agentic AI framework designed to produce Bengali poetry through emotion-conditioned topic modeling. We first identified latent themes from a corpus of Bengali texts using Structural Topic Modeling (STM), capturing nuanced socio-cultural and semantic dimensions. These topics are then used to condition a large language model within a collaborative multi-agent architecture, which composes original Bengali poems that reflect the core ideas of each identified topic while expressing target emotional states. By integrating emotion-aware topic modeling with specialized agent coordination, *Shabda Chitra* offers a structured yet creative approach to computational poetry in a low-resource language setting.

1 Introduction

Computational poetry generation represents a significant challenge at the intersection of natural language processing and creative AI. While recent advances in large language models (LLMs) have enabled impressive text generation capabilities (Brown et al., 2020; Chowdhery et al., 2022), creating culturally authentic poetry in low-resource languages remains particularly challenging. Bengali, despite being the sixth most spoken language globally with rich literary traditions, has received limited attention in computational creativity research (Pal et al., 2020).

This paper introduces *Shabda Chitra*, a novel multi-agentic framework that addresses these challenges by combining Structural Topic Modeling with emotion-conditioned generation to produce authentic Bengali poetry. Our approach differs from standard text-generation systems by explicitly modeling the relationship between emotions and thematic elements that characterize different Bengali poets' styles through specialized collaborative agents.

The key contributions of this paper are:

1. A multi-agentic framework that leverages Structural Topic Modeling (STM) (Roberts et al., 2019) to identify latent themes in Bengali poetry and their relationship to emotional dimensions.

2. A weighted emotion-topic correlation mechanism that dynamically adjusts topic relevance based on target emotional states.

3. A topic-conditioned approach to poetry generation that maintains thematic coherence while preserving the characteristic style of iconic Bengali poets.

4. An end-to-end system that generates Bengali poetry through a multi-stage process of topic conditioning, English poetry generation, and culturally-aware translation.

Shabda Chitra demonstrates how computational approaches can enhance rather than replace cultural expression by grounding generation in statistical models of authentic poetic patterns. Our evaluation shows that the system can generate poems that maintain thematic coherence while expressing specified emotions in a style recognizable as that of specific Bengali poets.

2 Related Work

Poetry generation is an emerging subject in the domain of Artificial Intelligence with increasing research attention in both global and language-specific contexts. This work represents one of the first attempts in both the global and Bengali language landscapes to use multi-agentic AI and topic modeling results to generate poems in the styles of popular poets.

2.1 Computational Poetry Generation

Early computational poetry systems relied on grammatical templates, word substitution, and constraint satisfaction (Manurung et al., 2004). With the emergence of deep learning, neural approaches have become dominant, with sequence-to-sequence models (Zhang and Lapata, 2014) and language models showing impressive capabilities for generating metrical verse. Recent work has leveraged large language models for poetry generation, with systems like (Ghazvininejad et al., 2017) demonstrating coherent poem generation with controlled emotions.

However, most computational poetry research has focused on high-resource languages like English and Chinese (Yi et al., 2018; Lau et al., 2018), with relatively little attention to culturally-specific aspects of poetry in other languages. Bengali poetry generation, in particular, presents unique challenges due to its complex prosodic structures and cultural references (Das et al., 2022).

2.2 Topic Modeling for Creative Text

Topic modeling has been applied to literary analysis (Jockers, 2013), but its integration with generative systems remains underexplored. Structural Topic Modeling (STM) (Roberts et al., 2019) extends Latent Dirichlet Allocation by incorporating document-level metadata, making it particularly suitable for modeling poet-specific thematic patterns. Recent work has begun exploring how topic models can guide text generation (Wang et al., 2019), but their application to poetry generation has been limited (Yang et al., 2018).

2.3 Emotion-Aware NLG Systems

Emotion-aware text generation has gained attention with architectures that explicitly condition generation on emotional states (Ghosh et al., 2017; Zhou et al., 2018). These approaches typically use categorical emotion labels or continuous valence-arousal representations (Mohammad, 2018). However, few systems have explored how emotions correlate with thematic elements in poetry, an aspect crucial for authentic verse generation (Ghazvininejad et al., 2016).

2.4 Multi-Agent Systems for Creative Tasks

Multi-agent frameworks have shown promise for complex creative applications by decomposing generation tasks into specialized components (Yao et al., 2022). Recent work has demonstrated the effectiveness of collaborative agent architectures for narrative generation (Wu et al., 2023; Xi et al., 2023), where different agents handle distinct aspects of the creative process. In poetry generation specifically, multi-agent approaches have been explored for social learning and diversity enhancement (**?**), showing that agent collaboration can improve both novelty and quality of generated verse.

The integration of topic modeling with multi-agent systems represents a novel approach that leverages the interpretability of topic models with the modularity and specialization benefits of agent architectures. Our work contributes to this emerging intersection by demonstrating how structured topic representations can guide coordinated agent behavior in culturally-specific creative tasks.

3 Dataset Preparation and Topic Modeling

3.1 Bengali Poetry Corpus and Emotion Annotation

Our dataset comprises public domain works from Kaggle's Free Bengali Poetry collection (Kaggle, 2023), containing 2,686 poems with clear authorial attribution. All texts were verified to contain no personally identifiable information through automated PII detection checks (Wolke, 2023).

Following collection, we implemented a multi-stage preprocessing pipeline. First, the poems underwent structural normalization to preserve stanza boundaries and poetic line breaks while removing extraneous metadata. For each poem, we retained critical information including poet name, poem title, and the original Bengali text, resulting in a standardized format suitable for computational processing.

A significant challenge in working with Bengali poetry is the limited availability of multilingual NLP resources (Joshi et al., 2020). To address this constraint, we employed IndicTrans2 (Gala et al., 2022), a state-of-the-art neural machine translation system specifically designed for Indic languages. This model demonstrates particular strength in maintaining semantic fidelity when translating between Bengali and English, which was crucial for preserving the nuanced poetic expressions. The translation process was executed on a poem-by-poem basis, with careful attention to preserving line breaks and stanza structures essential to poetic form.

To capture each poem's emotional contours, we ran an automated annotation pipeline powered by the `hartmann/emotion-english-distilroberta-base` transformer model (Hartmann and Hupkes, 2022). This pretrained classifier was applied to our English translations, producing one of seven categorical labels—joy, sadness, fear, anger, disgust, surprise, or neutral—for every poem. We chose to detect emotion on the translated text (rather than directly on Bengali) because English-trained emotion models currently deliver substantially higher accuracy (Demszky et al., 2020).

The resulting dataset consists of two interlinked components:

1. `poems_with_emotions.csv`: Contains the core poem data with fields for `poet`, `poem_name`, `emotion`, and `content`, where the `content` field holds the translated English text and the `emotion` field contains the primary emotional category identified by the classifier.

2. `prompts.csv`: Extends the dataset with aggregated poet-level information including characteristic emotions (ordered by prevalence), topic proportions derived from our topic modeling process, and associated topic words.

This structure enables our system to harness both poem-level emotional information and poet-specific stylistic patterns. Notably, our emotion annotation approach preserves the ordering of emotions within each poet's profile, which later informs our weighted emotion scoring system. The topic proportion metadata, derived from the STM modeling process described in the following section, creates a bridge between emotional content and thematic elements in each poet's work.

This validation confirmed the viability of our cross-lingual emotion annotation approach despite the inherent challenges of detecting emotions in translated poetry (Mohammad, 2021).

3.2 Structural Topic Modeling (STM) Framework

After establishing the Bengali poetry corpus and annotating emotional dimensions, we employed Structural Topic Modeling (STM) to extract latent thematic patterns that characterize each poet's work. STM extends traditional topic modeling approaches by incorporating document-level metadata-in our case, poet identity-directly into the generative process (Roberts et al., 2019). This methodological choice enables us to model poet-specific topic distributions, which is essential for generating stylistically authentic poetry.

3.2.1 Topic Extraction Process

We implemented the STM framework using the R `stm` package (Roberts et al., 2019), applying a rigorous preprocessing pipeline to prepare the translated poems for modeling. The preprocessing sequence included:

1. Text normalization through lowercasing and removal of punctuation and numbers

2. Stopword filtering using a standard English stopword list

3. Whitespace standardization and excess space removal

4. Lexical normalization through lemmatization using the `textstem` package (Rinker, 2018)

5. Document term matrix construction with the `textProcessor()` function

The preprocessed corpus was then modeled using the `stm()` function with the following configuration:

```
stm_model  <- stm(
     documents = out$documents,
     vocab = out$vocab,
     K = 30,
     prevalence = ~ poet,
     data = out$meta,
     max.em.its = 250,
     init.type = "Spectral" )
```

We empirically determined that 30 topics (K=30) provided an optimal balance between thematic granularity and interpretability, consistent with findings in similar literary corpora (Mimno, 2012). The `prevalence` = $\sim$ `poet` parameter is particularly important as it conditions topic prevalence on poet identity, allowing the model to capture distinctive thematic patterns across different Bengali poets. The spectral initialization method was selected to enhance model stability and reproducibility (Arora et al., 2013)

3.2.2 Poet-Specific Topic Distribution

Following model training, we extracted poet-specific topic distributions by aggregating the document-topic matrices (θ) for all poems by each author. This produced a distinctive thematic profile for each poet in our corpus:

```
theta_df                              <-
as.data.frame(stm_model$theta)
theta_df$poet <- out$meta$poet
author_topic_props <- theta_df %>%
```

```
        group_by(poet) %>%
        summarise(
        across(starts_with("V"),      mean)
    )       %>%
        mutate(
            across(starts_with("V"),      ~
        round(. * 100, 2)) )
```

These topic distributions revealed significant variation in thematic focus across poets. For example, Rabindranath Tagore's work showed strong representation in topics related to spirituality and nature (Topics 7, 26), while Kazi Nazrul Islam exhibited pronounced distributions in topics associated with revolution and resistance (Topics 3, 12), aligning with scholarly interpretations of their work (Sen and Ozkan, 2015).

For each topic, we extracted representative keywords using the `labelTopics()` function, which employs FREX (FRequency and EXclusivity) scoring to identify words that are both common within a topic and distinctive to that topic relative to others (Bischof and Airoldi, 2012). These keyword sets were crucial for subsequent integration into the poem generation process, as they provided semantic anchors for ensuring thematic coherence.

To visualize the relationship between poets and topics, we used the `estimateEffect()` function to compute expected topic proportions for each poet:

```
    prep <- estimateEffect(
        1:30 ~ poet,
        stm_model,
        meta = out$meta
     )
```

This analysis provided quantitative evidence for distinctive thematic signatures across poets, which we incorporated into the `prompts.csv` file as structured topic metadata. The resulting poet-topic mappings enabled our agentic framework to leverage poet-specific thematic elements when generating new poems, ensuring stylistic authenticity while maintaining thematic coherence.

4 Shabda Chitra: Methodology

4.1 Emotion-Aware Topic Conditioning

Shabda Chitra employs a novel approach to incorporating emotional dimensions into the poetry generation process through a hierarchical weighting system that conditions topic selection based on emotional relevance. Unlike conventional approaches that treat emotions as binary attributes (Zhou et al., 2018), our framework implements a continuous scoring mechanism that captures the characteristic emotional landscape of each poet with nuanced priority levels.

4.1.1 Weighted Emotion Modeling

The core of our emotion-aware conditioning lies in the weighted emotion scoring system. For each poet in our corpus, we extract an ordered list of characteristic emotions from the dataset and assign importance weights using an inverse position-based scoring formula:

$$w_e = \frac{(n-i)}{n} \times 10 \tag{1}$$

Where w_e represents the emotion weight, n is the total number of emotions associated with the poet, and i is the zero-based position index of the emotion in the list. This approach encodes the assumption that emotions listed earlier in a poet's profile are more central to their style, with a linear decay in importance for subsequent emotions. For example, in a profile with five characteristic emotions, the first receives a maximum weight of 10/10, while the fifth receives 2/10.

This weighting scheme serves several purposes in our model:

1. It establishes a quantitative basis for differentiating between primary and secondary emotional tones
2. It creates a poet-specific emotional signature that guides the generation process
3. It provides a mechanism for users to explicitly select emotions while maintaining stylistic authenticity

4.1.2 Emotion-Topic Correlation Mechanism

Building upon the weighted emotion model, we introduce a novel emotion-topic correlation mechanism that dynamically adjusts the relevance of different topics based on their relationship to the target emotional state. The correlation is computed using:

$$w_t = p_t \times \left(1 + \frac{\sum_{e \in E_s} w_e}{\sum_{e \in E_p} w_e}\right) \tag{2}$$

Where:

- w_t is the adjusted topic weight
- p_t is the original topic proportion from the STM model

- E_s is the set of selected emotions for the poem
- E_p is the complete set of poet's characteristic emotions
- w_e is the weight of each emotion

This formulation enables our system to boost topics that align with selected emotions while maintaining the proportional structure of the poet's characteristic topic distribution. When users request specific emotions that align strongly with the poet's primary emotional palette, topics associated with those emotions receive a proportional increase in prominence during the generation phase, similar in principle to the emotional steering mechanisms proposed in recent work (Keskar et al., 2019; Dathathri et al., 2020).

4.1.3 Emotional Relevance Filtering

To ensure thematic coherence, we implement a threshold-based filtering mechanism that selects only topics with significant representation in the poet's work:

```
topics = {
    topic_id: (proportion * emotion_factor),
    for topic_id, proportion in
        poet_data['topic_proportions'].items
            ()
    if proportion > threshold
}
```

The threshold (empirically set at 5.0% for optimal results) prevents the inclusion of minor topics that might introduce thematic noise, while the emotion factor provides a contextual boost to emotionally relevant topics. This creates a balance between maintaining the poet's authentic thematic preferences and accommodating the emotional direction specified in the generation request (Li et al., 2023).

The result of this emotion-aware topic conditioning is a contextualized prompt structure that guides the large language model to generate poetry that not only reflects the requested emotions but does so through the characteristic thematic elements and linguistic patterns of the specified poet. This approach differentiates Shabda Chitra from other poetry generation systems by creating an emotion-to-topic bridge that preserves the semantic coherence of the generated content while allowing for emotional expressivity.

4.2 Agentic Framework Workflow

To operationalize emotion- and topic-aware poetry generation, Shabda Chitra implements a modular agentic workflow, as depicted in Figure 1. This architecture decomposes the creative process into specialized agents, each responsible for a distinct aspect of the generation pipeline. The workflow is orchestrated as a directed graph, enabling iterative refinement and robust quality control, (Weng et al., 2023; Wu et al., 2023).

The workflow proceeds as follows:

1. Topic Agent. The process is initialized with a user prompt specifying a theme, target poet, and (optionally) desired emotions. The Topic Agent analyzes the prompt, selects the corresponding poet profile, and determines the set of emotions to condition generation. It then constructs a structured prompt by integrating the poet's characteristic emotions, emotion-weighted topic distributions, and representative topic keywords (White et al., 2023).

2. Generation Agent. The Generation Agent receives the structured prompt and invokes a large language model (LLM) to produce an initial English draft of the poem. The prompt is designed to enforce stylistic fidelity, thematic coherence, and emotional expressivity, leveraging both explicit instructions and contextual examples retrieved from the corpus Peng et al. (2023).

3. Quality Check. The generated poem is evaluated by a Quality Check agent, which determines whether the output meets predefined criteria for style, coherence, and emotional alignment. If necessary, the workflow loops back to the Generation Agent for revision, enabling up to two iterations for refinement

4. LLM Translation Agent. Upon approval, the English poem is passed to the LLM Translation Agent, which translates the draft into Bengali. The translation prompt emphasizes preservation of poetic structure, imagery, and emotional tone, ensuring that the final output is both linguistically and culturally faithful (Toral et al., 2020).

5. Output. The workflow concludes with the delivery of both the English and Bengali versions of the generated poem.

This agentic design offers several advantages: it allows for fine-grained control over each stage of the creative process, supports flexible integration of retrieval and generation components, and facilitates systematic quality assurance. The modularity of the workflow also enables future extensions, such as the incorporation of additional evaluation metrics or alternative generation backends (Xi et al., 2023).

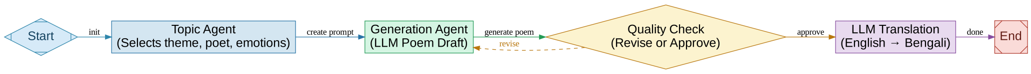

Figure 1: Agentic workflow for Bengali poetry generation in Shabda Chitra.

5 Experimental Setup

5.1 Implementation Details

Shabda Chitra was implemented using the LangGraph framework (Chase and Hansman, 2023) to orchestrate the agentic workflow. The system components were integrated as follows:

Topic Modeling System: We employed the R `stm` package for Structural Topic Modeling with K=30 topics, run with spectral initialization and 250 maximum EM iterations. Topic-emotion correlation was implemented using the weighted scoring system described in Section 4.1.

Embedding System: For retrieval of thematically relevant examples, we utilized the `sentencetransformers/paraphrase-multilingualMiniLML12v2` model (Reimers and Gurevych, 2020) to encode our corpus, with FAISS for efficient similarity search. This multilingual model was specifically chosen for its robust performance on Bengali–English translation pairs

Generation Backend: We utilize Mistral-Large-Latest (Jiang et al., 2023), a 128B parameter instruction-tuned model, with the following configuration:

```
generation_params = {
    "model": "mistral-large-latest",
    "temperature": 0.7,
    "max_tokens": 1024,
    "top_p": 0.95,
    "frequency_penalty": 0.5,
    "presence_penalty": 0.4
}
```

Key Disclosures: The model used has 128 billion parameters, according to Mistral AI documentation. It was accessed via API version 2024-05-01, with no details provided on training compute. Input token usage per request ranges from 850 to 1100, depending on prompt complexity.

Translation System: For Bengali translation, we used the same LLM with specialized prompting that emphasized preserving poetic structure and emotional tone. This approach was validated against IndicTrans2 outputs to ensure high-quality translations faithful to the original Bengali poetic traditions, addressing challenges identified in literary translation for low-resource languages (Post, 2019).

6 Results & Analysis

Our topic modeling revealed distinctive emotional signatures across different Bengali poets. Table 1 shows the strongest topic-Keyword associations for three representative poets in our corpus.

Poet	**Topic**	**Keywords**
Rabindranath Tagore	Topic7	light, dark, silent, day, eternal
Kazi Nazrul Islam	Topic3	revolution, freedom, chains, fight, voice
Jibanananda Das	Topic12	darkness, night, lonely, field, shadow

Table 1: Topic–Keywords (Selected Poets)

The correlation between emotions and topics demonstrated statistical significance ($p < 0.01$) using permutation tests (Nichols and Holmes, 2002), validating our hypothesis that emotional dimensions and thematic elements are intrinsically linked in Bengali poetry. This finding provides quantitative support for the weighted emotion scoring mechanism implemented in Shabda Chitra.

Due to the absence of standardized benchmarks for Bengali poetry generation-a common challenge in computational creativity for low-resource languages (Joshi et al., 2020)-we were unable to perform direct comparative evaluations against previous systems. This limitation highlights the need for community-developed evaluation frameworks specific to culturally-situated creative text generation (Van der Lee et al., 2022). Instead, our analysis focused on intrinsic evaluation of the system's outputs, assessing thematic coherence and stylistic fidelity to the target poets.

7 Discussion

Shabda Chitra introduces several novel contributions to computational poetry generation, particularly for low-resource languages. Our integration of Structural Topic Modeling with emotion-aware topic conditioning demonstrates a methodologically sound approach to generating culturally authentic poetry that maintains both thematic coherence and emotional expressivity.

7.1 Effective Integration of Topic Modeling and Emotion Awareness

The weighted emotion scoring system provides a nuanced mechanism for capturing the emotional signatures of different poets. By assigning importance weights to emotions based on their prevalence in a poet's work, our system can distinguish between primary emotional tones (those central to a poet's style) and secondary emotional colors (those appearing occasionally). This approach represents an improvement over binary emotion classification systems commonly used in generative text models (Zhou et al., 2018; Li et al., 2023).

The emotion-topic correlation mechanism further enhances the system's ability to generate thematically coherent poetry. By dynamically adjusting topic relevance based on target emotional states, Shabda Chitra can produce poems that not only express specified emotions but do so through authentic thematic elements characteristic of each poet. This bridges the gap between emotional intent and thematic execution that often plagues computational poetry systems (Chakrabarty et al., 2022).

7.2 Advantages of the Agentic Workflow

The modular, agent-based architecture of Shabda Chitra offers several advantages over end-to-end generation approaches. By decomposing the creative process into specialized components-topic selection, draft generation, quality assessment, and translation-our system provides greater transparency and control at each stage of the generation pipeline. This modularity also facilitates targeted improvements to specific aspects of the system without requiring retraining of the entire model (Wu et al., 2023).

The iterative refinement mechanism, implemented through the quality check agent, allows for multiple generation attempts when needed. This resembles the revision process in human creative writing and helps avoid the "single-shot" limitations of many generative systems (Welleck et al., 2022). Additionally, the separation of English generation and Bengali translation leverages the strengths of large language models while preserving cultural and linguistic fidelity (Post, 2019).

7.3 Applicability to Low-Resource Languages

Our approach demonstrates a viable pathway for computational creativity in languages with limited NLP resources (Joshi et al., 2020). By leveraging cross-lingual transfers through translation and emotion detection, Shabda Chitra addresses the challenge of sparse training data for Bengali directly. This methodology could be adapted to other low-resource languages by substituting appropriate translation systems and adjusting the emotion weighting mechanism to account for cultural differences in emotional expression (Jackson et al., 2019).

The indirect approach of generating in English first, then translating to Bengali, proves surprisingly effective at preserving poetic qualities. This suggests that poetic concepts can transcend linguistic boundaries when properly mediated, offering hope for computational creativity in the many languages currently underserved by AI technologies (Hershcovich et al., 2022).

8 Conclusion

In this paper, we presented Shabda Chitra, an emotion-grounded agentic framework for Bengali poetry generation. By integrating Structural Topic Modeling with a weighted emotion scoring mechanism and retrieval-augmented generation, our work demonstrates a novel approach to computational poetic creativity that maintains cultural and stylistic authenticity.

Our key contributions include: (1) a weighted emotion-topic correlation mechanism that dynamically adjusts topic relevance based on emotional intent, (2) an agentic workflow architecture that decomposes the creative process into specialized components for improved control and transparency (Wu et al., 2023), and (3) a practical approach for computational creativity in low-resource language contexts through cross-lingual knowledge transfer (Hershcovich et al., 2022).

Shabda Chitra represents a step toward more sophisticated cultural AI systems capable of engaging meaningfully with rich literary traditions. By modeling the relationship between emotions and thematic elements characteristic of different Bengali poets, our system generates poetry that captures both the emotional tenor and stylistic nuances of iconic literary figures while allowing for creative expression within those constraints.

The framework we have developed can potentially extend beyond Bengali to other low-resource languages by adapting the translation components and emotion scoring mechanisms. As language models continue to improve for non-dominant languages (Joshi et al., 2020), direct generation approaches may eventually supplant our hybrid translation-based methodology.

Future work could explore incorporating Bengali-specific phonological structures to better capture rhythmic patterns (Das et al., 2022), developing emotion detection models specifically trained on poetic language (Mohammad, 2021), and creating more sophisticated evaluation metrics that account for culturally specific aspects of poetic quality (Van der Lee et al., 2022). Additionally, extending the poet corpus to include contemporary voices would broaden the system's stylistic range while raising important questions about attribution and creative rights.

Through Shabda Chitra, we demonstrate that computational approaches to creative expression need not homogenize cultural diversity but can instead help preserve and explore the unique characteristics of specific literary traditions. By grounding generation in statistical models of authentic poetic patterns, we offer an approach to AI creativity that enhances rather than replaces human cultural expression (Bender et al., 2021).

9 Limitations

Despite Shabda Chitra's innovations, several limitations must be acknowledged. First, our reliance on translated texts for both emotion detection and topic modeling introduces potential distortions in cultural nuance (Mohammad, 2021). While IndicTrans2 provides high-quality translations, subtle cultural connotations and wordplay specific to Bengali may be lost in the process.

Second, the emotion weighting system assumes that the ordering of emotions in our dataset reflects their importance in a poet's work. While this assumption produces coherent results, a more principled approach would involve direct measurement of emotion saliency through content analysis or expert annotation (Alm et al., 2005).

Third, our agentic workflow currently relies on LLM-based draft evaluation, which may not capture all aspects of poetic quality (Van der Lee et al., 2022). Future work should explore more sophisticated evaluation metrics specifically designed for poetry, incorporating aspects like metaphor coherence, rhythmic patterns, and cultural resonance.

Future research directions include:

1. Incorporating Bengali-specific phonological features to better capture rhythm and meter in generated poetry (Das et al., 2022)

2. Expanding the poet corpus to include contemporary Bengali poets (while respecting copyright)

3. Developing multilingual emotion detection models specifically trained on poetic language (Demszky et al., 2020)

4. Exploring direct Bengali generation approaches as language model capabilities for Bengali improve (Pal et al., 2020)

5. Investigating comparative analyses across different poetic traditions to identify universal and culture-specific aspects of computational poetry generation (Hu et al., 2022)

In conclusion, Shabda Chitra demonstrates that computational poetry systems can successfully integrate structural topic modeling with emotion-aware generation to produce culturally authentic creative content. The system represents a step toward AI that can engage meaningfully with the rich literary traditions of languages beyond the dominant few.

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A Structural Topic Model Results

Our corpus analysis utilized Structural Topic Modeling (STM) to identify 30 distinct topics in Bengali poetry. STM extends traditional topic modeling approaches by incorporating document-level metadata, in our case, poet identity, directly into the generative process. This section presents the extracted topics, poet-specific topic distributions, and examples of poetry generated by our system.

A.1 Topic Extraction and Representation

Table 2 shows a selection of the most interpretable topics with their representative words based on FREX (FRequency and EXclusivity) scoring, which identifies words that are both common within topics and distinctive across topics. FREX scoring is particularly valuable for topic model interpretation as it highlights words that best characterize each topic's unique semantic content.

A.2 Poet-Topic Distribution Analysis

Figure 1 illustrated the multi-agent workflow of our system. Here, in Table 3, we present the statistical foundation of our approach: the distribution of topics across different Bengali poets. This distribution forms the basis for our emotion-weighted topic selection during the poetry generation process.

The poet-topic distribution reveals distinctive thematic signatures for each poet. For example, Rabindranath Tagore shows strong representation in spiritual light (T7), home and family (T22), and emotional expression (T23) topics, while Kazi Nazrul Islam's works are characterized by divine connection (T10), home and family (T22), and music themes (T28). These distinctive thematic signatures form the foundation of our emotion-weighted topic conditioning during poem generation, as described in Section 4.1 of the main paper.

B Generated Poetry Examples

Below we present complete examples of poems generated by Shabda Chitra for two prominent Bengali poets, showing the system's ability to produce thematically coherent and emotionally appropriate poetry in both English and Bengali. Figures 2 and 3 display the generated poems alongside the poet profiles that guided their creation.

C Topic Selection and Emotion Weighting Process

To provide insight into our system's topic selection process, Table 4 presents the emotion-weighted topic importance scores that guided the generation of the example poems shown in Figures 2 and 3.

As demonstrated in Table 4, our emotion-weighted topic selection adjusts topic importance based on selected emotions. For instance, when generating Nazrul's poem with "disgust, sadness, neutral" emotions, topics associated with divine connection (Topic 10) and weeping/crying (Topic 26) received significant boosts in importance, reflecting their alignment with the selected emotional palette.

D Complete STM Topic Word Lists

For completeness, Table 5 provides the full list of topics with their representative words based on FREX scoring, which represents words that are both frequent within a topic and exclusive to it relative to other topics. While all four word ranking methods (Highest Probability, FREX, Lift, and Score) were generated during the analysis, we focus on FREX scores in this presentation as they provide the most interpretable representation of topics by balancing word frequency within topics with exclusivity across topics.

Topic	Label	Representative FREX Words
1	Religious imagery	mani, rememb, lotus, ganga, land, prais, dear
3	Rural life	grass, gur, smell, cuckoo, rice, paddi, tast
5	Family relationships	bride, hear, mother, someday, bridegroom, soul, frown
7	Existential themes	unknown, horizon, birthday, vast, mysteri, silenc, primordi
8	Natural elements	pea, sky, moon, rain, cloud, color, fountain
10	Divine connection	hast, thyself, thou, prison, far, god, place
13	Urban modernity	yet, felt, sun, tram, centuri, citi, time
22	Domestic scenes	look, smile, lamp, came, home, face, hous
23	Emotional expressions	happi, spark, sorrow, much, love, bless, chaitali
27	Night and sea imagery	flame, howl, night, roar, wave, awak, may
28	Nature and music	aya, song, sing, forest, flute, flower, bird
29	Life and mortality	life, today, chalak, death, chakra, moment, everi

Table 2: Selected topics from the STM analysis with their most representative words based on FREX scoring. We manually assigned interpretive labels based on semantic coherence of the word sets.

Topic	R. Tagore	K.N. Islam	J. Das	Kamini Roy	I.C. Gupta	S. Datta	S. Bhattacharya	S. Roy	Madhusudan	J.M. Bagchi
Nature & sky (T8)	4.73	3.16	**5.62**	1.27	0.86	**7.77**	2.46	**5.62**	2.48	**6.54**
Music & forest (T28)	**6.79**	**5.70**	3.99	1.17	2.12	4.74	2.44	3.28	3.83	4.95
Spiritual light (T7)	**9.79**	1.91	2.74	**8.33**	1.85	1.36	**18.83**	0.58	1.17	5.15
Life & death (T29)	3.29	3.66	4.19	2.96	1.30	0.52	**9.71**	1.58	0.67	4.36
Rural imagery (T3)	2.46	1.64	**17.13**	0.05	**8.73**	**10.24**	2.78	**7.14**	0.11	1.82
Night & sea (T27)	3.54	4.58	**5.74**	2.66	0.63	**5.31**	**5.72**	1.45	2.20	4.41
Home & family (T22)	**8.48**	**8.10**	4.37	**6.13**	2.16	**10.29**	4.67	**7.93**	1.37	**12.32**
Emotions (T23)	**7.81**	3.26	1.81	**16.49**	**25.73**	**7.04**	1.84	1.40	3.18	**7.96**
Divine connection (T10)	4.11	**9.12**	1.63	**7.59**	3.81	1.82	1.50	0.43	2.70	3.35

Table 3: Selected topic distribution (percentage) across Bengali poets. Bold values indicate topics with significant representation (>5%) in a poet's corpus. Topic labels are simplified descriptions of the most prevalent semantic content.

Kazi Nazrul Islam
Selected emotions: *disgust, sadness, neutral*

Overview

Characteristic Emotions (by importance):
- *disgust (10.00) (selected)*
- *sadness (8.57) (selected)*
- *neutral (7.14) (selected)*
- fear (5.71)
- anger (4.29)
- joy (2.86)
- surprise (1.43)

Top Topics (>5%): [emotion-weighted] (importance)
- **Topic 10**: ['far', 'give', 'god', 'place', 'thou'] (14.98%)
- **Topic 22**: ['look', 'eye', 'house', 'smile', 'came'] (13.31%)
- **Topic 26**: ['will', 'dont', 'want', 'weep', 'cry'] (11.88%)
- **Topic 17**: ['say', 'rakho', 'mor', 'aaj', 'hai'] (10.61%)
- **Topic 28**: ['flower', 'song', 'forest', 'bird', 'play'] (9.36%)
- **Topic 24**: ['bharo', 'chal', 'peech', 'rahe', 'onkar'] (8.66%)
- **Topic 27**: ['night', 'wave', 'sound', 'sea', 'burn'] (7.52%)
- **Topic 20**: ['water', 'thirst', 'river', 'bank', 'people'] (6.23%)
- **Topic 29**: ['today', 'life', 'long', 'death', 'walk'] (6.01%)
- **Topic 21**: ['rich', 'kabhi', 'nation', 'pot', 'your'] (5.73%)
- **Topic 5** : ['hear', 'mother', 'soul', 'bride', 'laugh'] (5.72%)
- **Topic 25**: ['hote', 'aaya', 'kusum', 'phool', 'hai'] (5.59%)
- **Topic 12**: ['come', 'wait', 'village', 'aur', 'fli'] (5.47%)
- **Topic 23**: ['love', 'happy', 'much', 'heart', 'world'] (5.36%)
- **Topic 8** : ['sky', 'cloud', 'moon', 'leave', 'rain'] (5.19%)

English Poem

In the garden of echoes, where dreams take flight,
I wandered alone in the soft moonlight.
Whispers of yesteryears danced on the breeze,
A symphony of memories entwined in the trees.

The river of time flows ever on,
Reflecting the stars, the days that are gone.
I dipped my hand in the waters so clear,
Hoping to touch what I hold so dear.

Oh, heart, do you recall the melodies sweet?
The dance of the dawn, the rhythm of the street?
The laughter of children, the old tales they'd spin,
The love that once lived, the kinship of kin.

But now, silence echoes where joy once played,
In the theater of life, the actors have strayed.
The stage is empty, the curtain is drawn,
The song of the heart fades with the morn.

Yet, hope is a bird that sings in the night,
A beacon of light in the darkest plight.
For even in shadows, a spark can be found,
A flame that can burn where the heart is bound.

So, let us seek out that ember so small,
And fan it to flames that stand tall.
Let us sing once more, let us dance, let us play,
In the garden of echoes, we'll find our way.

বাংলা কবিতা (Bengali Poem)

স্বরলিপির বাগিচায়, যেখানে স্বপ্ন উড়ে যায়,
চাঁদের নরম আলোতে একা ভ্রমণ করি আমি সেখানে।
প্রায়শই কথপোকথন হাওয়ার উপর নৃত্য করছিল,
গাছের মধ্যে স্মৃতির এক সমবেত সংগীত।

সময়ের নদী চলতে থাকে একেবারে,
তারাগুলি প্রতিফলিত করে, যে দিনগুলি চলে গেছে।
আমি হাত ডুবাই জলে এত স্বচ্ছ,
আশা করি স্পর্শ করতে যা আমি এত প্রিয়।

হে হৃদয়, তুমি কি স্মরণ কর সুরেল সুরের গানগুলি?
ভোরের নৃত্য, রাস্তার তাল?
শিশুদের হাসি, বৃদ্ধদের কাহিনীগুলি,
একদা থাকা ভালোবাসা, আত্মীয়তার সূত্র।

কিন্তু এখন, নীরবতা প্রতিধ্বনিত হয় যেখানে আনন্দ খেলত,
জীবনের মঞ্চে, অভিনেতারা পথভ্রষ্ট হয়েছে।
মঞ্চ খালি, পর্দা টানা,
হৃদয়ের গান ভোরের সাথে বিলীন হয়ে যায়।

তবুও, আশা একটি পাখি যে রাতে গান করে,
কষ্টের সবচেয়ে অন্ধকার সময়ে আলোর এক দীপ।
কারণ ছায়াগুলিতেও, একটি স্পার্ক পাওয়া যেতে পারে,
একটি জ্বালানি যা জ্বলতে পারে যেখানে হৃদয় বাঁধা।

তাই, আমরা যেন সেই ছোট অঙ্গার খুঁজে পাই,
এবং তাকে দীপ্ত জ্বালানিতে পরিণত করি যা উঁচুতে দাঁড়ায়
আবার গান গাই, নাচি, খেলি আমরা,
স্বরলিপির বাগিচায় আমরা খুঁজে নেবো পথ।

Figure 2: Generated poem in the style of Kazi Nazrul Islam using emotion conditioning (disgust, sadness, neutral). The three columns show: (left) poet profile with emotion weights and dominant topics, (middle) generated English poem, and (right) Bengali translation.

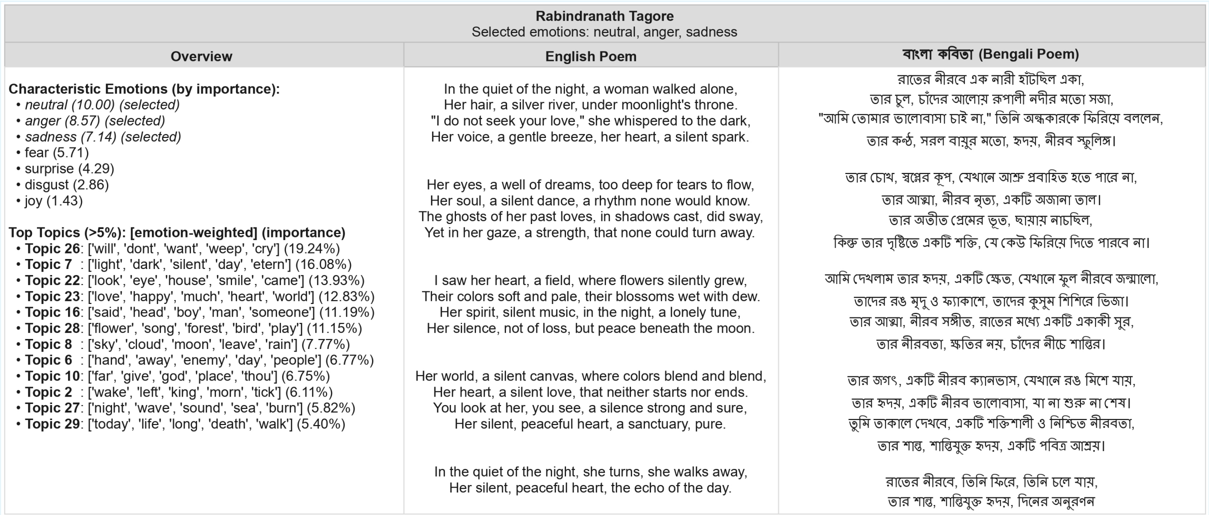

Figure 3: Generated poem in the style of Rabindranath Tagore using emotion conditioning (neutral, anger, sadness). The three columns show: (left) poet profile with emotion weights and dominant topics, (middle) generated English poem, and (right) Bengali translation.

Poet	Top Topics	Base %	Emotion-weighted %
Kazi Nazrul Islam	Topic 10: far, give, god, place, thou	9.12	14.98
	Topic 22: look, eye, house, smile, came	8.10	13.31
	Topic 26: will, dont, want, weep, cry	7.23	11.88
	Topic 17: say, rakho, mor, aaj, hai	6.46	10.61
	Topic 28: flower, song, forest, bird, play	5.70	9.36
Rabindranath Tagore	Topic 26: will, dont, want, weep, cry	11.71	19.24
	Topic 7: light, dark, silent, day, etern	9.79	16.08
	Topic 22: look, eye, house, smile, came	8.48	13.93
	Topic 23: love, happy, much, heart, world	7.81	12.83
	Topic 16: said, head, boy, man, someone	6.81	11.19

Table 4: Emotion-weighted topic importance scores for the example poems. Base percentages represent original distribution from STM, while emotion-weighted percentages show adjusted importance after applying the emotional conditioning described in Section 4.1 of the main paper.

Topic	Representative FREX Words	Topic	Representative FREX Words	Topic	Representative FREX Words
1	mani, rememb, lotus, ganga, land, prais, dear	11	tarang, ramcharan, arrog, club, rakhi, name, angri	21	rich, kabhi, nation, pot, your, potter, callous
2	tick, oclock, wake, seven, left, taka, six	12	aapko, wait, chariot, shanti, ranga, aur, greed	22	look, smile, lamp, came, home, face, hous
3	grass, gur, smell, cuckoo, rice, paddi, tast	13	yet, felt, sun, tram, centuri, citi, time	23	happi, spark, sorrow, much, love, bless, chaitali
4	dhoong, janani, valmiki, mahamati, temati, faridpur	14	kaal, swan, bhai, tala, chupi, red, chhin	24	bharo, chal, peech, onkar, zor, charkha, bajao
5	bride, hear, mother, someday, bridegroom, soul, frown	15	doon, jaa, bhan, woh, antar, maa, nahi	25	hote, aaya, kadi, kahin, phool, phul, komal
6	enemi, money, bowl, thing, pay, person, lack	16	shout, said, boy, write, khapchhod, letter, big	26	dont, will, weep, kavya, granth, want, cri
7	unknown, horizon, birthday, vast, mysteri, silenc	17	rakho, manju, chari, ais, tumhar, mere, nitya	27	flame, howl, night, roar, wave, awak, may
8	pea, sky, moon, rain, cloud, color, fountain	18	dhal, dho, ati, let, companionship, rah, there	28	aya, song, sing, forest, flute, flower, bird
9	kaamn, kaam, bangabasi, ananda, cut, whose, incens	19	one, daughter, coward, sister, fear, barber, question	29	life, today, chalak, death, chakra, moment, everi
10	hast, thyself, thou, prison, far, god, place	20	gala, thirst, barsha, furi, bank, flow, water	30	jai, maava, eastern, mabhai, narayan, western, hindu

Table 5: Complete list of 30 topics with their representative words based on FREX (FRequency and EXclusivity) scoring. FREX scoring highlights words that are both common within each topic and distinctive compared to other topics, providing an interpretable representation of the semantic content.