AI-Powered Tarot Reading Using NLP and Sentiment Analysis

Soe Htet Naing[1], Min Marn Ko[2], Phue Pwint Thwe[3]
[1]Asian Institute of Technology
Department of Computer Science and Information Management
Data Science and Artificial Intelligence
{st125166, st125437, st124784}@ait.asia

Abstract

This study explores the application of Natural Language Processing (NLP) and sentiment-aware AI models for personalized Tarot readings. Traditional Tarot readings rely on human intuition and predefined interpretations, but this project aims to automate and personalize the process using AI-driven text generation. Our approach integrates user input (question & zodiac signs), sentiment detection (BERT), and a fine-tuned GPT-2 model to generate refined Tarot readings. The proposed system is evaluated based on accuracy, engagement, personalization, and thematic coherence. This research contributes to interactive AI applications, personalized AI-driven storytelling, and emotion-aware content generation.

1 Introduction

1.1 Background of the study

Tarot readings have been used for centuries to provide insights, guidance, and personal reflections. With the rise of AI-driven content generation, there is an opportunity to automate and personalize Tarot readings while retaining their symbolism and interpretative depth. Advancements in NLP, particularly in text generation, sentiment analysis, and personalization, provide an opportunity to create dynamic and engaging AI-powered fortune readings. By integrating astrological, numerological, and psychological principles with modern AI methods, we aim to improve context relevance, engagement, and adaptability.

1.2 Problem Statement

Traditional fortune-telling methods rely on intuition and predefined templates, making them non-adaptive to user preferences. Most AI-generated content lacks personalization and context-awareness, making it feel generic and unconvincing. Existing Tarot reading bots typically rely on predefined text templates, failing to integrate user sentiment and individual zodiac insights into the prediction.

1.3 Research Objective

This study proposes an AI-powered Fortune Teller that leverages NLP models and sentiment-aware prediction systems to generate customized and meaningful fortunes. The model integrates astrology, numerology, and psychological profiling to create adaptive and engaging predictions.

1.4 Expected Outcomes

We hypothesize that:

1. Sentiment-aware Tarot readings will improve user engagement and satisfaction.

2. Fine-tuned GPT-2 Tarot text generation will be more coherent and diverse than static templates.

3. Personalized readings (zodiac-based adaptation) will enhance credibility and believability.

1.5 Solution Requirements

For an AI-generated tarot reading system to be effective, it must meet several critical requirements. Personalization is a key factor, ensuring that the system adapts dynamically based on user inputs, such as birth date, name, and emotional sentiment. By incorporating these factors, the AI model can generate contextually relevant and meaningful fortune readings tailored to individual users. Additionally, engagement plays a vital role in enhancing user experience. The AI-generated fortunes should be entertaining, thought-provoking, and non-generic, ensuring sustained user interest and emotional connection.

Furthermore, authenticity is crucial in establishing credibility and trust among users. The AI model must integrate real astrological and numerological principles, drawing from structured datasets and traditional knowledge to enhance the depth and reliability of generated predictions. This integration helps bridge the gap between traditional fortune-telling practices and modern AI-driven text generation. Finally, ethical considerations must be carefully addressed to ensure responsible AI deployment. The system should avoid generating misleading, overly deterministic, or negative predictions, which could lead to unintended psychological or emotional impacts on users. Implementing sentiment-aware filters and ethical AI guidelines can help ensure that the generated content remains constructive and beneficial.

1.6 Contributions

This study introduces a novel application of NLP in the domain of tarot reading, leveraging advanced text generation techniques to create personalized predictions. By combining deep learning, rule-based modeling, and user-driven customization, this research pioneers a framework that enhances traditional fortune-telling through AI. Additionally, we propose an integrated AI framework that fuses natural language generation, sentiment analysis, and astrology-based modeling to ensure contextually appropriate and engaging predictions. This interdisciplinary approach aims to improve user experience while maintaining the depth and richness of traditional fortune-reading practices.

To evaluate the effectiveness of AI-generated fortunes, we conduct a structured comparative analysis between AI-generated and human-created fortune readings. The evaluation considers key factors such as coherence, engagement, personalization, and sentiment accuracy. Through both qualitative and quantitative assessment methodologies, this study provides insights into the capabilities and limitations of AI-driven text generation in entertainment, psychological well-being, and personalized user experiences.

2 Research Questions

The primary objective of this research is to explore how NLP techniques can be utilized to enhance contextual relevance, engagement, and authenticity in AI-generated fortune readings. A key challenge lies in ensuring that the generated predictions align with cultural and user expectations while preserving the entertainment value inherent in traditional fortune-telling practices. Additionally, sentiment analysis plays a significant role in modulating the tone of predictions, influencing user engagement and satisfaction. Another crucial aspect is the integration of astrological and numerological insights, requiring a balance between data-driven predictions and traditional metaphysical knowledge. This study seeks to address these challenges by formulating the following research questions:

1. How can sentiment-aware NLP models enhance the personalization of AI-generated Tarot readings?
2. What is the impact of zodiac-based adaptation on the perceived authenticity of Tarot predictions?
3. How does an AI-generated Tarot reading compare to human-created interpretations in terms of coherence and engagement?

This research aims to establish a foundation for human-centered AI-powered tarot readings, ensuring relevance, adaptability, and user trust through responsible AI development.

3 Literature Review

3.1 Tarot Reading and AI

Recent advancements in AI have enabled computational models to explore the domain of predictive analytics, often drawing comparisons with traditional fortune-telling techniques. Research has highlighted the role of machine learning in forecasting trends, behaviors, and future events based on historical data. The study by (Liu et al., 2016) explores AI-driven predictions in career trajectory modeling, emphasizing the potential of neural networks and decision trees in providing insights into individual career paths. However, ethical concerns persist regarding AI's role in making personal predictions, especially in domains associated with belief systems like astrology and fortune-telling.

Beyond career predictions, NLP models have begun to explore text generation for spiritual and metaphysical domains, such as astrology, numerology, and tarot readings. Studies such as Xu et al. (2022) demonstrate how AI can analyze astrological data for predictive insights. Engagement and diversity in fortune-telling AI can be enhanced through storytelling techniques, retrieval-augmented generation (RAG), and deep-learning-based symbolic interpretations. Furthermore, hybrid models that integrate symbolic AI with neural networks show promise in authentic and personalized fortune readings (Zhang Lee, 2021).

Current AI-based fortune-telling models lack contextual understanding. This study aims to enhance engagement and authenticity through fine-tuned generative models and sentiment-aware personalization.

3.2 Text Generation in Entertainment AI

Text generation has become a significant focus in entertainment AI, with applications spanning storytelling, scriptwriting, and humor generation. The study by (Li et al., 2023) evaluates AI-generated humor in traditional Chinese comedic performances, highlighting the challenges in producing humor that aligns with human expectations. Similarly, (Piper, 2023) discusses AI's role in automated storytelling, emphasizing multimodal narrative understanding and cultural narrative schemas.

While GPT-2 and similar models have demonstrated strong text generation capabilities, they require fine-tuning on specialized datasets to produce meaningful, structured Tarot interpretations.

3.3 Sentiment Analysis in AI-generated Content

The proliferation of AI-generated content has necessitated advanced sentiment analysis models to assess and regulate emotional tonality. Research on AI-generated text detection, such as that by (Yadagiri et al., 2024), explores methods to differentiate AI-generated content from human-written text using linguistic and statistical features. Moreover, studies on sentiment evaluation in AI-generated content suggest that pre-trained transformer models, including BERT and RoBERTa, can effectively assess sentiment polarity, ensuring quality control in AI-driven media. Another relevant work by (Sun et al., 2024) investigates iterative AI refinement techniques in text generation, which can influence the emotional tone and coherence of AI-produced narratives.

For fortune-telling applications, sentiment analysis plays a crucial role in enhancing user experience and engagement. AI-generated readings must balance realism with optimism, ensuring that users receive constructive and emotionally appropriate guidance. Research on emotion-aware embeddings, reinforcement learning-driven sentiment modulation, and affective computing techniques suggests that AI can tailor fortune readings based on real-time emotional feedback (Pawar et al., 2024). Additionally, dynamic response generation and tone-adjustment algorithms can enhance engagement by ensuring a positive user experience.

Sentiment-aware AI models have been successfully implemented in chatbots and recommendation systems, but their application in Tarot readings remains unexplored.

4 Methodology

4.1 Proposed Model Architecture

The proposed system follows a structured NLP pipeline, as shown below:

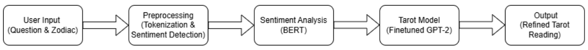

Figure 1: Overview of the Project Framework

1. User Input: The system receives user questions and zodiac sign information.
2. Preprocessing: Tokenization and sentiment detection are performed on the user input.
3. Sentiment Analysis (BERT): The sentiment classifier detects positive, neutral, or negative emotions.
4. Tarot Model (Fine-tuned GPT-2): The model generates a Tarot interpretation tailored to user sentiment and zodiac characteristics.
5. Output: The final refined Tarot reading is displayed to the user.

4.2 Dataset

To develop an AI-powered Tarot reading system, we employed a combination of structured fortune-telling texts, sentiment-annotated dialogue datasets, and user-specific features to train and fine-tune our models. The dataset construction was designed to ensure both traditional Tarot reading authenticity and user personalization through sentiment and astrological insights.

4.2.1 Primary Dataset: Tarot Readings Dataset

The primary dataset utilized in this study is the Tarot Readings Dataset sourced from Hugging Face. This dataset provides structured Tarot interpretations, encompassing the following key components:

- Card Names: Includes all 78 Tarot cards, capturing both upright and reversed positions.
- Interpretations: Contextual readings tailored for different aspects of life (e.g., love, career, personal growth).
- General Fortune Predictions: Standard text-based Tarot readings used in traditional Tarot practices.

4.2.2 Extended Dataset: Personalized Tarot Dataset

To enhance personalization and engagement, we extended the Tarot Readings Dataset by incorporating additional user-specific features. These augmentations enable AI-generated predictions to align with individual user attributes. The extended dataset includes:

- User Birth Date: Extracted and mapped to zodiac signs to incorporate astrological influences.
- Sentiment-Based Variations: AI-generated Tarot readings tailored to positive, neutral, and negative emotional states.
- Custom Fortune Templates: AI-augmented text samples designed to increase diversity and personalization in the generated Tarot readings.

4.2.3 Dataset Statistics

Dataset	Source	Size	Features
Tarot Readings Dataset	Hugging Face	10,000+ entries	Tarot card meanings, interpretations
Personalized Tarot Dataset	AI-Generated	5,000+ entries	Birth date, zodiac signs, sentiment-based readings

Table 1: Dataset composition for Tarot reading generation

Figure 2: Sentiment Analysis Model

4.3 Data Preprocessing

Before training the models, data preprocessing is essential to ensure consistency, accuracy, and contextual relevance. The preprocessing pipeline will involve text cleaning, where unnecessary symbols and HTML tags are removed, followed by tokenization using WordPiece (BERT-based) and Byte Pair Encoding (GPT-2-based) techniques to enhance lexical representation. Additionally, a Named Entity Recognition (NER) model will be employed to extract key user attributes, such as birth date and zodiac sign, mapping them to corresponding astrological influences. TF-IDF and keyword extraction techniques will further categorize user intent (e.g., love, career, health) for improved personalization. To integrate sentiment-awareness, a BERT-based sentiment classifier will be fine-tuned to label user queries as positive, neutral, or negative, ensuring that Tarot readings align with emotional context. This preprocessing phase will provide a structured, sentiment-aware, and user-personalized dataset for model training.

4.4 Model Training

The Tarot reading system will be trained using a dual-model approach, consisting of a BERT-based sentiment analysis model and a GPT-2-based text generation model. The sentiment analysis model shown in figure 2 will be fine-tuned on annotated sentiment datasets, classifying user inputs into positive, neutral, or negative categories, enabling context-aware response generation. The text generation model, based on GPT-2, will be fine-tuned on a combination of the Tarot Readings Dataset and the Personalized Tarot Dataset, allowing for engaging, dynamic, and coherent Tarot predictions. Training will be conducted using the Hugging Face Transformers library, leveraging an NVIDIA A100 GPU for optimization. The GPT-2 model will be optimized using Adam optimizer with a learning rate of 5e-5, while the sentiment classifier will use AdamW with a learning rate of 3e-5. This approach will ensure that the generated Tarot readings are linguistically coherent, sentiment-aware, and personalized based on user attributes.

4.5 Evaluation

To evaluate the effectiveness of the AI-generated fortune readings, the system will be assessed using both quantitative and qualitative metrics.

4.5.1 Quantitative Metrics

The model's text generation quality will be evaluated through several key metrics. Perplexity (PPL) will be used to measure the fluency and readability of generated text, ensuring that the model produces grammatically coherent sentences. BLEU Score, a widely used metric in NLP, will assess text coherence and accuracy by comparing AI-generated fortunes with human-written references. Additionally, a Diversity Score will be calculated to evaluate the uniqueness of AI-generated fortunes, ensuring that the model produces varied and engaging predictions rather than repetitive or generic outputs.

4.5.2 Qualitative Metrics

To complement the quantitative evaluation, human assessment will be conducted. Human evaluation will involve user surveys and ratings to assess engagement, authenticity, and satisfaction with the AI-generated fortunes. Additionally, sentiment consistency will be analyzed to determine whether the AI-generated fortunes align with user emotional states and exhibit an appropriate tone based on input parameters.

4.5.3 Baselines

To benchmark the performance of the proposed model, comparisons will be made against existing static rule-based fortune generators, which rely on predefined templates and deterministic algorithms. Additionally, the system's performance will be compared with general GPT-based text generation models that have not been fine-tuned on astrological or numerological data. These baseline comparisons will provide insight into the advantages of fine-tuning NLP models with structured metaphysical knowledge and sentiment analysis.

By combining quantitative, qualitative, and comparative evaluations, this study aims to demonstrate the effectiveness of NLP-driven, personalized fortune readings, ensuring that the generated content is contextually relevant, diverse, and engaging for users.

5 Task Distribution

For this project proposal phase, our team members contributed the tasks according to the table 2.

Task	Responsible Member	Description
Literature Review	Soe Htet Naing Min Marn Ko Phue Pwint Thwe	Reviewing ACL papers and summarizing relevant works
Dataset Collection	Soe Htet Naing Min Marn Ko	Gathering astrology, numerology, and sentiment-annotated text data
Model Training	Min Marn Ko Phue Pwint Thwe	Choosing GPT-based models and training sentiment analysis module
Evaluation Metrics	Soe Htet Naing Phue Pwint Thwe	Designing assessment methods and benchmarking performance
Report Writing	Soe Htet Naing Min Marn Ko Phue Pwint Thwe	Documenting methodology, results, and discussions

Table 2: Task Distribution for the Project

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