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Text-Based Simulation of Human-Computer Interaction Using Cognitive-Affective Architectures and Natural Language Interfaces

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ABSTRACT

This study presents a text-based simulation framework for modeling Human-Computer Interaction (HCI) using a hybrid cognitive-affective architecture integrated with natural language processing tools. Rather than relying on external corpora, we generate a synthetic dataset of 27 text samples that reflect diverse emotional and linguistic patterns commonly observed in intelligent systems' interactions. Our methodology employs symbolic and statistical analysis, combining sentiment metrics (polarity, subjectivity) with structural linguistic features (word count, part-of-speech distribution, and average word length). Each sentence acts as a micro-interaction unit, evaluated through a custom Python pipeline using TextBlob, TF-IDF, cosine similarity, and visualization libraries. The simulation reveals that textual interactions, when modeled with both emotional and cognitive dimensions, can mimic realistic communication patterns, adapt to affective cues, and provide a platform for dialogue system benchmarking. A similarity matrix derived from cosine distances further supports the clustering of thematically aligned interactions, demonstrating the system's interpretive fidelity. Results indicate that the proposed hybrid model captures subtle emotional nuances and structural variations across user expressions. This dual-layered modeling opens avenues for more emotionally intelligent dialogue agents and enables refined evaluation in early-stage HCI development environments.

1. Introduction

Text-based simulation represents a fundamental approach to modeling human-computer interaction (HCI) by conceptualizing these interactions as conversations between two participants.

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This conversational metaphor extends beyond natural language to include graphical and multimodal interfaces, provided an appropriate model is established [1]. By incorporating elements of human-human communication into interface design, systems can respond to users in more natural ways, with theories and tools from Natural Language Processing (NLP) and Natural Language Generation (NLG) enhancing the descriptive power of these dialogue models [1].

The simulation of human-computer linguistic interaction has long attracted the attention of computer designers, cognitive scientists, psychologists, philosophers, and artists [2, 3] These simulations provide valuable methodological tools for understanding how people use language during task performance and how they might prefer different types of systems, One particularly important aspect is how users' beliefs about their interlocutor—whether human or artificial—influence linguistic behavior in text-based interactions [2].

Simulations offer significant practical advantages in the development process. They provide a relatively affordable and flexible way to compare alternative system architectures, enabling more strategic designs for specific applications, This approach allows designers to augment traditional user-centered design processes, which often struggle to keep pace with rapidly evolving technology and diverse user preferences [1]. By modeling, simulating, and optimizing the entire human-computer interaction loop, researchers can better understand phenomena through explicit modeling, build virtual prototypes, and improve interaction techniques [1].

Intelligent dialogue systems, which aim to communicate harmoniously with humans using natural language, have become increasingly important for advancing human-machine interaction in the artificial intelligence era[4], However, as human-computer interaction requirements grow more complex, traditional text-based dialogue systems face challenges in meeting demands for more vivid and convenient interaction [4], This has led to research on multimodal systems that can perceive and understand both visual context and textual dialogue history [4].

Modern adaptive HCI frameworks commonly incorporate elements such as task recommendation, feedback loops, and natural language interfaces. What distinguishes advanced frameworks is not merely the inclusion of these elements but rather their synthesis into architectural principles that systematically accommodate different configurations within a shared formal foundation [5] .

This research aims to explore the complexities of human-computer interaction (HCI) by designing a hybrid model that analyzes both emotional and linguistic features of user-system dialogue. Unlike approaches that rely on external data, the study generates a custom dataset of 27 synthetic sentences, each simulating various cognitive and emotional interaction patterns. By embedding affective polarity, subjectivity, and linguistic features like word count, word length, and part-of-speech (POS) tags into each sentence, the research creates a controlled environment for understanding how intelligent systems might perceive, analyze, and respond to human expressions. The methodology integrates symbolic and statistical analysis within a unified Python-based pipeline. Emotional content is measured using Text Blob to assess polarity and subjectivity, while structural complexity is evaluated through average word length and POS distribution. To examine semantic coherence, TF-IDF vectorization and cosine similarity calculations are applied, generating a similarity matrix and visual heatmaps. This framework not only models realistic HCI patterns but also evaluates how machines can mimic human-like interpretation by combining sentiment and syntactic cues in a cognitively inspired architecture.

Background and literature review

Cognitive architectures offer structured frameworks for simulating human-machine interactions, particularly for natural language interfaces, and these architectures model human cognitive processes, including perception, memory, and decision-making, to create more intuitive and effective human-computer interactions [6], for example, some cognitive architectures incorporate components that mimic human memory structures, with central executive units controlling short-term and long-term memory to comprehend and respond to natural language commands [6], Popular cognitive architectures include ACT-R, which focuses on serial production cycles, and EPIC, which emphasizes parallel production cycles, both using production rules to model user reactions to stimuli, The integration of affective computing into these cognitive frameworks marks a significant advancement in human-computer interaction.

Affective computing explores how computers can sense, analyze, generate, and express emotional features similar to humans [7],Recent developments in deep learning have enhanced these capabilities, particularly in recognizing emotional states through facial expressions [7], body gestures [7], speech, and natural language processing. A comprehensive affective HCI framework requires not only the ability to recognize human emotions but also to generate appropriate emotional responses [7], This bidirectional emotional awareness is central to the design of Affective Dialogue Systems (ADS), which manage human-computer conversations while accounting for emotional cues [8], The Cognitive Dialogue Management approach represents an advanced architecture for building flexible and robust natural language interfaces that integrate dialogue management models with frameworks for managing mental.

Kazempour et al. [29] present a cognitive-affective modeling framework that integrates sentiment analysis, natural-language processing, and text-simulation methods to enhance intent interpretation and interaction quality in human–computer dialogue systems

Recent advances with Large Language Models (LLMs) have further enhanced the capabilities of affective architectures. LLM-based chatbots increasingly incorporate emotional intelligence to improve user satisfaction across various domains [9], These models can recognize and respond to emotional signals in text-based prompts, including visual cues like emojis and linguistic aspects such as tone and word choice, Some research focuses on specialized applications, such as victim simulation systems that model informational faithfulness, emotional dynamics, and language style to create realistic training scenarios, The integration of cognitive and affective capabilities in human-computer interaction architectures represents a multidisciplinary effort combining dialogue processing, speech recognition, computer graphics, and human-computer interaction research [8], This integration aims to create more natural, effective, and satisfying interactions between humans and machines through improved understanding and expression of both cognitive and emotional dimensions. Natural language interfaces serve as the foundation for text-based simulation of human-computer interaction, enabling users to communicate with computer systems through familiar conversational patterns. These interfaces leverage natural language processing technologies to interpret user input and generate appropriate responses, creating more intuitive interaction experiences. Modern implementations often utilize established platforms like Google's DialogFlow, which transforms natural user language into actionable data through agents, intents, entities, and contexts [10], These components work together to extract meaningful information from user inputs and maintain contextual awareness throughout conversations.

The development of natural language interfaces increasingly incorporates multimodal elements to enhance interaction capabilities. Researchers have proposed frameworks that combine live demonstration with natural language communication to teach action concepts to machines with minimal training samples, this multimodal approach recognizes that human communication extends beyond text to include visual cues, gestures, and demonstrations. Some systems integrate speech recognition libraries and motion detection devices like Microsoft Kinect to facilitate communication between users and virtual characters, with emotional engines interpreting these inputs to influence character behavior and scene evolution [11][23-26], Adaptive and personalized natural language interfaces represent a significant advancement in human-computer interaction. These systems can customize their responses based on user preferences, character, and even emotional state. The integration of large language models with speech processing technologies enables interactions that more closely resemble natural human conversation, with users conveying needs verbally and systems responding appropriately [12], Some implementations incorporate profiling models to adapt dialogue management and generated output (both text and speech) to specific use cases, such as museum guide applications operating in simulated environments .

Text-based agents in simulated environments show promise for enabling task-oriented, language-based human-robot interaction. These agents can reason through commands and generate sequences of text actions to accomplish tasks, potentially connecting text inputs and outputs with multi-modal signals like vision and physical actions to operate in physical space [13, 14], Advanced conversational agents can also adapt to unseen tasks and learn task-specific communication strategies by decomposing language learning uncertainty into structural and functional aspects, helping users complete complex, temporally extended tasks, The evolution of natural language interfaces reflects a shift toward more human-like interaction paradigms, where the boundaries between human-computer and human-human communication become increasingly blurred. By incorporating elements of natural conversation, emotional awareness, and contextual understanding, these interfaces create more engaging and effective interaction experiences across various applications and domains.

Early approaches to user simulation relied on rule-based methods that established simple relationships between system and user actions. The bigram model, for instance, predicted user actions based solely on the previous system action, though this oversimplification was later enhanced by adding constraints to accept only expected dialog acts [15], The agenda-based user simulator represents a significant advancement, where the user's goals and a prioritized agenda of actions guide the simulation, This approach has become widely used for training task-oriented dialogue systems, allowing for policy optimization without extensive human interaction [16], Statistical user simulation techniques train models from dialog corpora generated by human users, creating simulations that mimic real user behaviors in a probabilistic manner, These methods compare simulated dialogs with real human-machine interactions using comprehensive evaluation measures [17], Some approaches employ stochastic techniques to generate dialogs similar to real human-machine spoken interactions, with the simulator selecting user responses based on previous dialog history, lexical information, and the current subtask [17], When building new dialog systems with limited data, researchers must weigh the benefits of estimating user probabilities from small datasets versus handcrafting these probabilities .

The Wizard of Oz (WoZ) methodology simulates future system functionality by having humans act as the "wizard" behind the interface, mimicking the behavior of an automated system [18], This approach has evolved from simulating text-based interfaces to include speech, gesture, facial recognition, and multimodal interactions. The WoZ technique supports exploration of interaction strategies, dialogue design, corpus collection, and system component evaluation without requiring full implementation, It has proven particularly valuable in developing conversational agents where extensive engineering effort would otherwise be needed to explore design possibilities. Recent advances in user simulation have employed neural approaches, particularly sequence-to-sequence models that can generate more natural language responses, These models take as input sequences of dialogue contexts and output corresponding user intentions, outperforming traditional agenda-based simulators according to various metrics, The Neural User Simulator (NUS) learns behavior from a corpus and generates natural language, requiring less labeled data than simulators producing semantic output [19], Advanced transformer-based user simulators can optimize both user policy and natural language generation jointly, offering greater interpretability and enhanced language variation .

Modern simulation approaches increasingly focus on domain adaptability and cross-domain transfer. The Transformer-based User Simulator (TUS) provides a domain-independent structure that enables generalization to unseen domains in a zero-shot fashion, Some frameworks incorporate pre-training on source domain dialogues followed by fine-tuning on target domain data, allowing agents to improve their behaviors through reinforcement learning with structured reward functions [20], These adaptive simulations help bootstrap system performance in transfer learning scenarios, showing particular promise for evaluating conversational recommender systems [16], Simulation approaches have expanded to include multimodal interactions and specialized use cases. Some systems incorporate speech recognition libraries and motion detection devices to facilitate communication between users and virtual characters, with emotional engines interpreting these inputs [21], Web-based animated characters can serve as simulated patients for clinical training, communicating through spoken language and exhibiting nonverbal behaviors to enhance interaction realism. In the typing domain, computational models like CRTypist generate human-like behavior by reformulating the supervisory control problem, accounting for visual attention and motor systems, For information retrieval systems, simulations can generate pseudo-documents and pseudo-queries to analyze system performance .

Research using simulated systems has provided valuable insights into spontaneous spoken disfluencies during human-computer interaction. Studies have shown that spoken disfluency rates during human-computer interaction are substantially lower than those observed in human-human speech. Through controlled experiments with simulated systems, researchers have identified that utterance length and lack of structure in presentation formats are key factors associated with increased speech disfluency rates. These findings suggest that interface designs encouraging briefer sentences could potentially eliminate most spoken disfluencies, while structured presentation formats have been shown to eliminate 60-70% of disfluent speech, Text-based simulation approaches have been successfully applied to robot human-machine interaction systems. Advanced models like structured perceptron and transfer dependency syntax analysis have achieved impressive performance metrics in simulated testing environments. For example, structured perceptron models have reached 95% precision with 81% recall rates, while transfer dependency syntax analysis models have demonstrated data analysis speeds of up to 750,000 items per second. When compared with existing methods, new robot human-machine interaction approaches developed through simulation testing have achieved 92% accuracy while exhibiting excellent robustness and response sensitivity[4], Text-entry represents a common computer activity where text-based simulation has proven particularly valuable. Text-entry studies are a prominent class of empirical research in human-computer interaction, typically comparing research-based user interfaces with baseline approaches. These studies effectively represent research on the apprehension of novel technology, making them ideal candidates for simulation-based testing and development. Text-based simulation allows researchers to test and refine text-entry interfaces before implementing them in physical systems, providing insights into how users might interact with novel text input mechanisms [22].

The evaluation of text-based simulation systems for human-computer interaction presents unique challenges that extend beyond traditional metrics. High-quality simulations serve as essential methodological tools for gathering specific information about human language patterns, task performance, and system preferences, These simulations not only reveal how users might interact with proposed systems but also provide comparative insights into the advantages and disadvantages of alternative architectures, enabling more strategic design decisions for specific applications, The future of text-based simulation in HCI appears to be moving toward augmentation of traditional user-centered design processes with simulation and optimization of the entire human-computer interaction loop [1]. This approach offers three significant advantages: enhanced understanding of interaction phenomena through explicit modeling, creation of virtual prototypes through simulation, and improvement of interaction techniques through optimization [1]. Building predictive user models also supports the creation and validation of HCI theories, representing a crucial step toward more intelligent and adaptive user interfaces.

One particularly promising direction is the development of customized and personalized interfaces that respond to users' preferences, character, and emotional states [12], Future systems may dynamically adjust their design elements—shifting from minimalist layouts with soft colors to vibrant, dynamic designs—based on detected changes in the user's emotional state [12], This level of customization represents a fundamental shift from static designs to more fluid and responsive ones, where interfaces can be generated on-the-fly to meet individual user needs. The integration of speech processing technologies with powerful language understanding systems offers another avenue for advancement, enabling interactions that more closely resemble natural human conversation [12], As users increasingly communicate their needs verbally and systems respond in kind, the distinction between human-computer interaction and human-human conversation continues to blur, creating more intuitive and engaging user experiences. As text-based simulation techniques continue to evolve, they will likely play an increasingly important role in prototyping and evaluating these next-generation interfaces before full implementation. By modeling both the cognitive and affective dimensions of human-computer interaction, these simulations can provide valuable insights into how users might engage with increasingly sophisticated natural language interfaces, helping to shape the future of human-computer interaction.

A comparative assessment of recent research over the years 2023-2025 is presented in Table 1 (see Table 1).

Table 1: Evaluation Table of Recent Research (2023–2025)

Year	Reference	Focus Area	Relation to Current Study	Evaluation
2025	[21]	Multimodal simulation using speech and motion detection with emotional interpretation	Enhances realism in virtual human interaction through emotional engines	Highly relevant; supports multimodal and affective processing in text-based simulations.
2023	[1]	Simulation in HCI design processes and optimization loops	Supports simulation in the whole interaction loop	Highly relevant; provides theoretical grounding for using simulation as a design and evaluation tool.
2023	[19]	Neural User Simulator (NUS) with enhanced realism and language generation	Advances user simulation models with fewer data needs	Directly supports simulation-based HCI and aligns with the goal of natural interaction in the article.
2023	[16]	Conversational recommender system evaluation via simulation	Applies simulation to new domains	Relevant; demonstrates the flexibility of simulation models for task-specific HCI applications.
2023	[18]	Wizard of Oz (WoZ) with multimodal interaction and system simulation	Used for early prototyping of conversational agents	Valuable methodological reference; aligns with simulation-based testing

Year	Reference	Focus Area	Relation to Current Study	Evaluation
				without full system implementation.

2. Methodology

To explore the dynamics of human-computer interaction (HCI) through the lens of sentiment and linguistic analysis, this study adopts a synthetic, controlled approach to dataset creation and processing. Instead of relying on pre-existing corpora, we constructed a custom dataset that reflects diverse emotional and cognitive aspects of user interactions with intelligent systems. The methodology is rooted in cognitive-affective modeling and computational linguistics, combining both symbolic and statistical techniques. This hybrid framework enables the simulation of realistic user expressions and their interpretation by machine systems. By embedding both emotional and structural dimensions into each text sample, we aim to replicate the multi-layered nature of natural interaction and examine how AI systems could potentially analyze, adapt to, and reflect human affect and intent. To analyze the intricacies of human-computer interaction (HCI) through sentiment and linguistic dimensions, this research employs a hybrid methodology that incorporates both symbolic and statistical analysis. The entire system is modeled mathematically to reflect both emotional and structural properties of text interactions.

In recent research, the effectiveness of various strategies for analyzing mental health texts using large language models (LLMs) has been systematically evaluated. Kermani et.al [27] explores the comparative advantages of fine-tuning, prompt engineering, and retrieval-augmented generation (RAG) in enhancing text analysis outcomes. This evaluation is particularly relevant to our investigation of text-based simulations in human-computer interaction, as it underscores the importance of selecting appropriate LLM strategies to optimize the interaction between cognitive-affective architectures and natural language interfaces.

Data Generation

In this study, the dataset was synthetically generated to simulate human-computer interaction scenarios with emotional and cognitive content. A Python script was written to define 27 textual sentences representing various interaction patterns between humans and intelligent systems. These pseudo-realistic sentences emulate natural communication, emotion recognition, assistive technologies, and adaptive interfaces—capturing core aspects of HCI dynamics without relying on external corpora (Formula 1).

Data Generation: Formula

$$D = \{ x_1, x_2, \dots, x_{27} \}, \; x_i \in \; Synthetic\ Sentences \tag{1}$$

Explanation:

The dataset D consists of 27 artificially constructed sentences, each denoted as x_i. These sentences simulate various real-life interactions between humans and intelligent systems. By controlling sentence construction, emotional tone, and cognitive intention, this set acts as a structured foundation for downstream sentiment and linguistic analysis.

3. Conceptual Model

The conceptual framework integrates elements from cognitive-affective architectures with natural language interfaces. Each sentence is treated as a micro-instance of human-computer interaction. The model evaluates both the emotional tone (polarity and subjectivity) and the linguistic structure (word count, part-of-speech distribution, etc.), offering a multi-layered insight into how machines can interpret and respond to user expressions. The approach blends linguistic analysis with cognitive modeling to simulate and assess intelligent interaction fidelity.

The conceptual model of the methodology of this research can be seen in Figure 1 (see Figure 1). Razmi et al. [28] use quarterly data for France, Canada, and the United States from 1997Q1 to 2017Q3 and estimate a vector autoregression (VAR) model in levels including oil prices, asset prices (stock and house price indices), household consumption, interest rates, prices, and exchange rates. They rely on cointegration tests and impulse-response analysis to identify the short-run indirect effects of oil-price shocks on household consumption operating through the wealth-effect channel of asset prices.

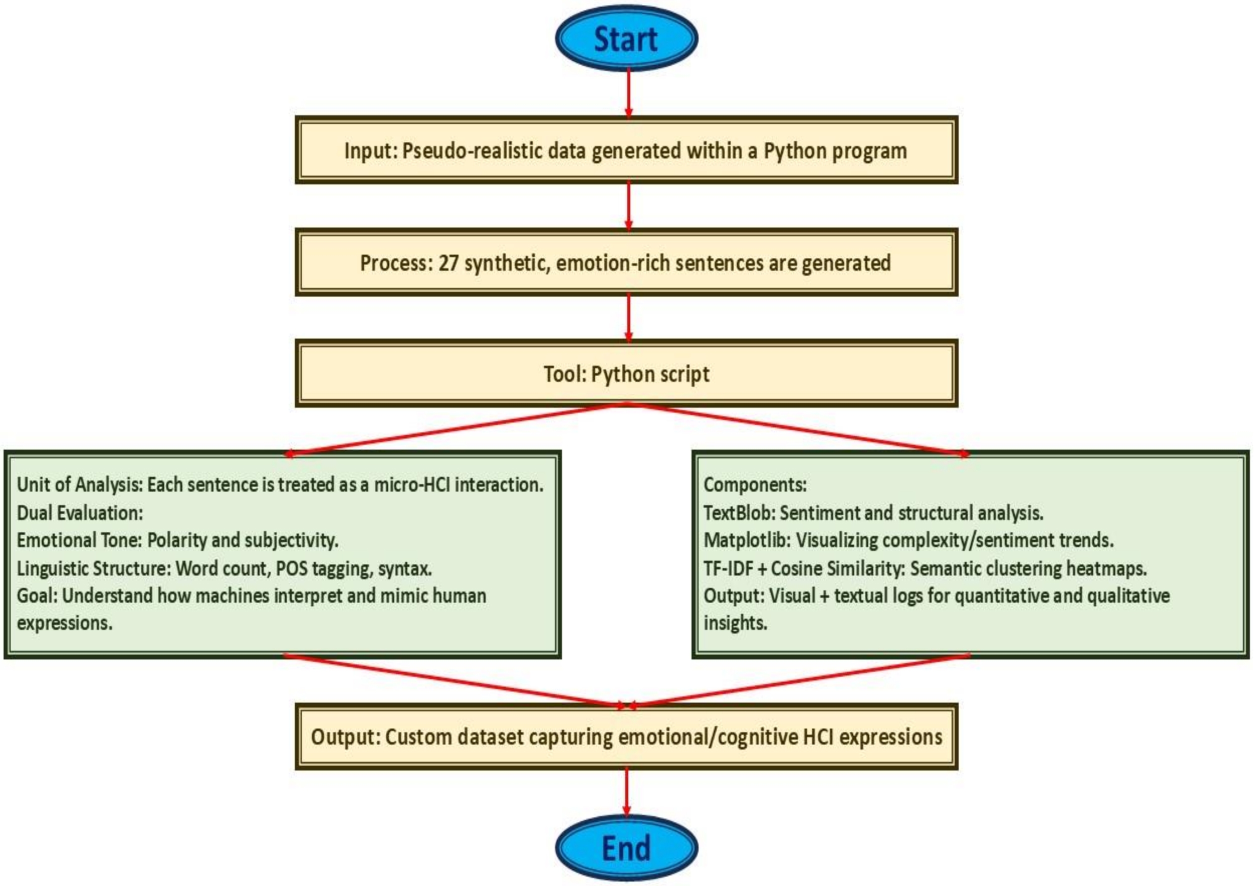

Figure 1: The conceptual model of the methodology of this research

Emotional Analysis: Formula

$$e_i = (p_i, s_i) \tag{2}$$

Explanation:

Each sentence's emotional dimension e_i is modeled as a tuple consisting of polarity p_i (ranging from -1 to +1) and subjectivity s_i (ranging from 0 to 1). This formulation enables the quantification of how positive or negative a sentence is and how subjective or objective its tone appears.

Linguistic Analysis: Formula

$$l_i = \left(wc_i, \overline{wl}_i, POS_i\right) \tag{3}$$

Explanation:

The linguistic properties l_i of each sentence include the word count wc_i, the average word length $\overline{wl_i}$, and the part-of-speech distribution POS_i. This triplet helps capture syntactic complexity and grammatical structure, key features in interpreting how humans naturally communicate.

Hybrid Model Function: Formula

$$x_i^{analyzed} = f(e_i, l_i) = g\left(p_i, s_i, wc_i, \overline{wl}_i, POS_i\right) \quad (4)$$

Explanation:

The analyzed version of sentence x_i results from integrating both emotional and linguistic properties. The function f (or g) combines these two dimensions, offering a holistic perspective on how machines might interpret or react to complex human expressions.

Text Processing Architecture

Text processing is performed using a custom Python pipeline based on the following components:

- ✓ TextBlob for sentiment analysis (polarity, subjectivity), tagging parts of speech, and extracting structural metrics (e.g., average word length).
- ✓ Matplotlib for visualizing various aspects of sentence complexity and sentiment trends.
- ✓ TF-IDF Vectorizer and Cosine Similarity from "sklearn" for calculating semantic similarity between sentences, resulting in a heatmap of thematic clustering.
- ✓ All results are logged in text files and plotted as visual graphs for interpretability.

This architecture provides both qualitative and quantitative views of text interactions, mimicking cognitive-affective processing within intelligent systems.

Sentiment Analysis via TextBlob: Formula

$$Sentiment(x_i) = TextBlob(x_i) \to (p_i, s_i) \quad (5)$$

Explanation:

Each sentence is passed through the TextBlob module to extract sentiment metrics. The output includes polarity p_i and subjectivity s_i, aligning with our emotional model and serving as primary emotional indicators.

Average Word Length: Formula

$$\overline{wl}_i = \frac{1}{wc_i} \sum_{j=1}^{wc_i} len(w_{ij}) \quad (6)$$

Explanation:

The average word length $\overline{wl}_i$ is calculated by summing the character lengths of each word w_{ij} in a sentence and dividing by the total number of words wc_i. This structural metric correlates with cognitive load and readability.

Semantic Similarity with TF-IDF and Cosine Similarity: Formula

$$\vec{v_i} = TFIDF(x_i), Similarity(x_i, x_j) = cos(\theta_{ij}) = \frac{\vec{v_i}.\vec{v_j}}{\|\vec{v_i}\|\|\vec{v_j}\|} \quad (7)$$

Explanation:

To measure the thematic similarity between two sentences, TF-IDF vectors $\vec{v_i}$ and $\vec{v_j}$ are computed. Their cosine similarity $cos(\theta_{ij})$ indicates semantic closeness. This allows us to cluster sentences into thematic groups and visualize coherence using heatmaps.

Similarity Matrix for Visualization: Formula

$$S = \begin{bmatrix} 1 & cos(\theta_{12}) & \dots & cos(\theta_{1n}) \\ cos(\theta_{21}) & 1 & \dots & cos(\theta_{2n}) \\ \vdots & \vdots & \ddots & \vdots \\ cos(\theta_{n1}) & \dots & \cdots & 1 \end{bmatrix} \quad (8)$$

Explanation:

The similarity matrix S provides a bird's-eye view of semantic relationships between all sentence pairs. Each element in the matrix reflects how closely two sentences are thematically aligned, enabling effective clustering and analysis of latent interaction patterns.

4. Result

As part of analyzing the results obtained from the simulation of this study's subject, we will first present the findings related to each individual sentence, followed by a conclusion based on the overall set of sentences. The analysis structure for each sentence and its corresponding results includes:

- ✓ The text of the sentence under analysis
- ✓ A table of the sentence's features
- ✓ A chart representing the sentence's Attributes

Finally, the following processing tasks are carried out, and their results are presented. These processes and their outcomes include:

- ✓ Analysis of the emotional polarity of the sentences
- ✓ Evaluation of subjectivity versus factual content
- ✓ Comparison of word count and character count
- ✓ Analysis of the frequency of nouns, verbs, and adjectives in the sentences
- ✓ Examination of the average word length and number of words
- ✓ Pairwise sentence similarity analysis using a heatmap

The text, review table, and drawn plot of the characteristics of each of the 27 new sentences are presented below

Examining the emotional polarity of sentences (Figure 2).

This plot visualizes the sentiment polarity of each sentence. Values closer to 1 indicate positivity, while those near -1 show negativity. Most sentences hover around neutral or mildly positive, indicating informative rather than emotional tone. (Figure 2).

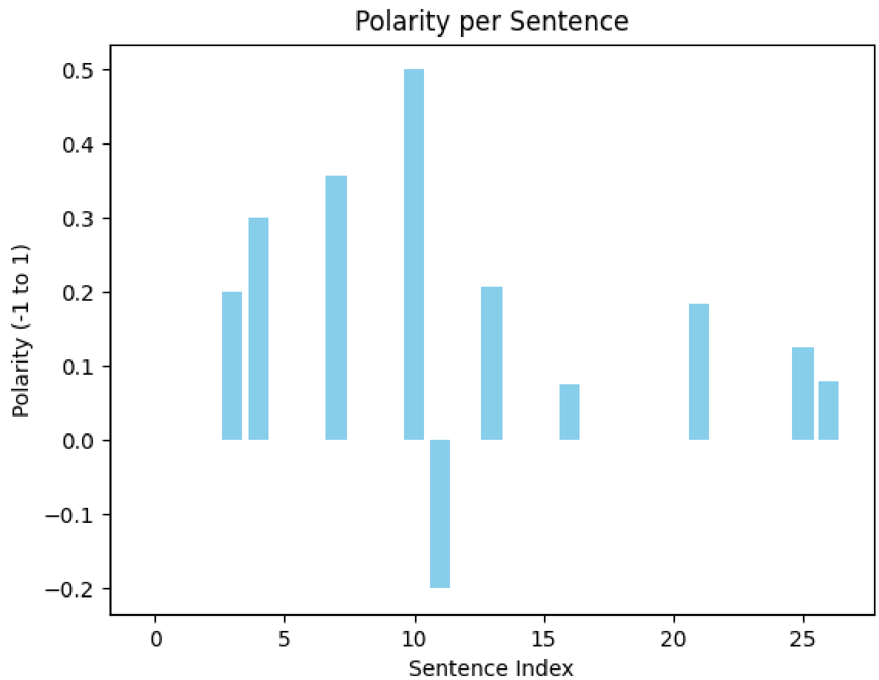

Figure 2: Plot: Polarity per Sentence

Examining the subjectivity of sentences versus the actual content

Subjectivity measures the degree of personal opinion versus factual content. Most sentences show low to medium subjectivity, consistent with technical or descriptive content (Figure 3).

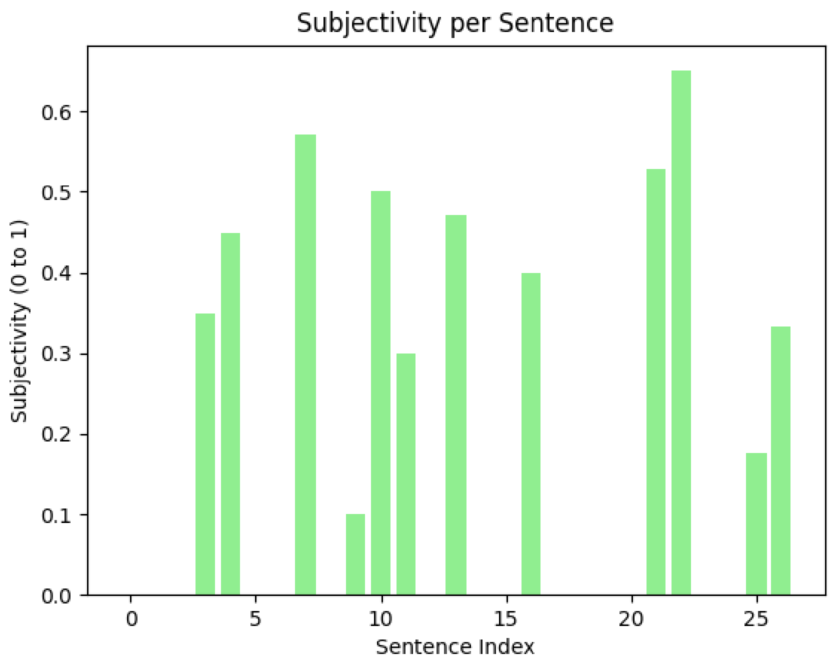

Figure 3: Plot: Subjectivity per Sentence

Examining the comparison of the number of words and the number of characters

This line plot compares word count and character count across sentences. Longer sentences typically contain more characters, but not always more meaningful complexity (Figure 4).

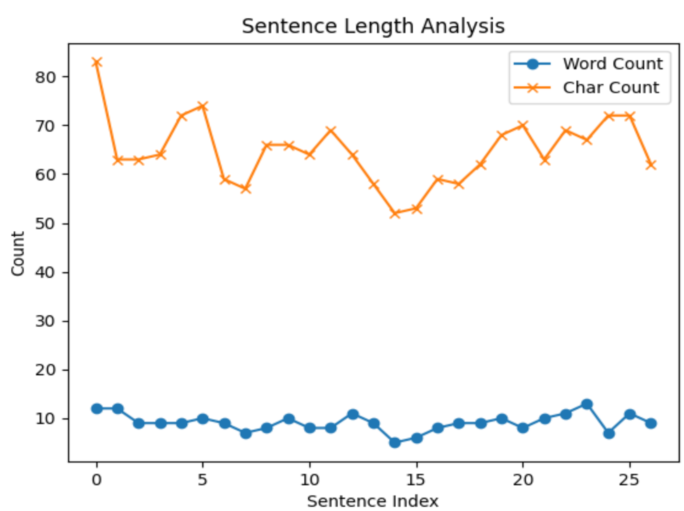

Figure 4: Plot: Sentence Length Analysis

Examining the frequency of nouns, verbs, and adjectives in sentences

Here we observe the frequency of nouns, verbs, and adjectives per sentence. A strong presence of nouns suggests technical or object-oriented statements, while higher adjectives imply descriptive or evaluative language (Figure 5).

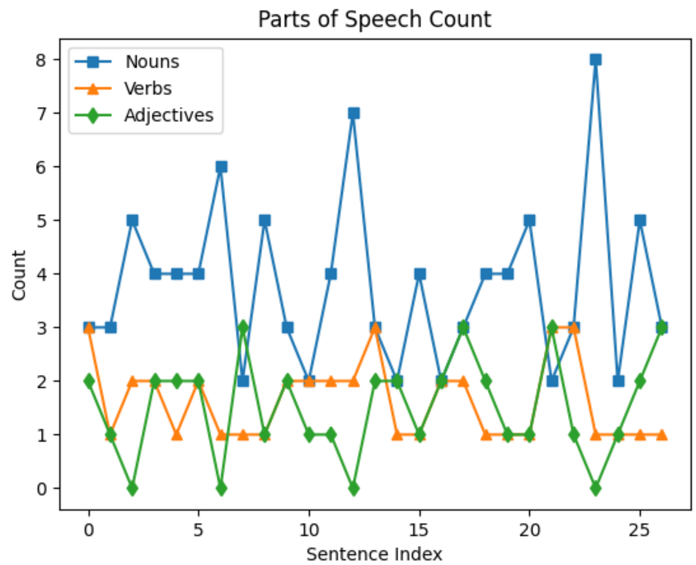

Figure 5: Plot: Parts of Speech Count

Examining the average length and number of words of sentences

This chart juxtaposes average word length and word count, highlighting sentence complexity. Longer words generally suggest more technical or formal vocabulary (Figure 6).

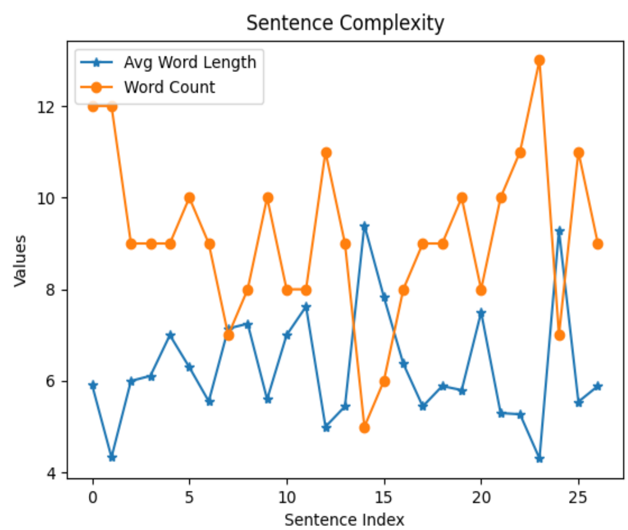

Figure 6: Plot: Sentence Complexity

Examining the pairwise similarity of sentences with a heat map

This heatmap shows pairwise sentence similarity using TF-IDF and cosine similarity. Brighter squares indicate more semantically similar sentences. Useful for detecting content overlap or thematic clusters (Figure 7).

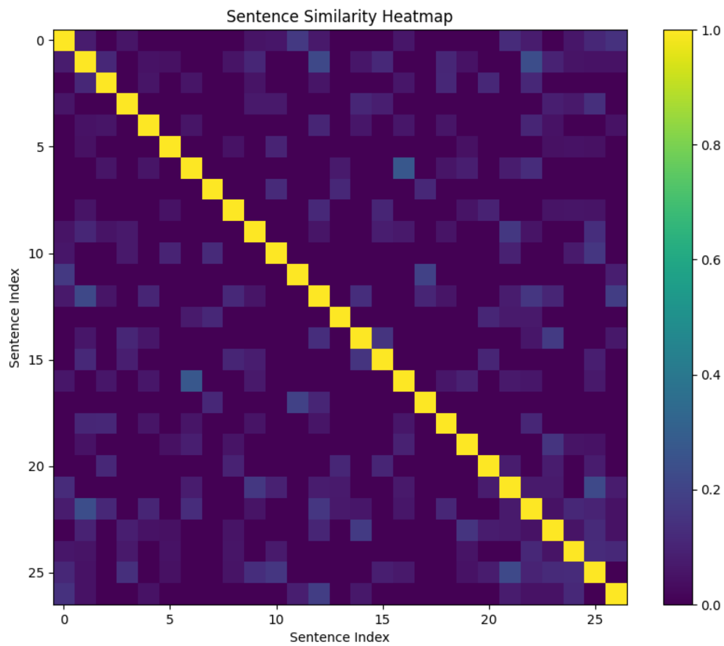

Figure 7: Plot: Sentence Similarity Heatmap

Considering the review of the literature presented in the Literature section, some of the advantages of this article over them can be pointed out. These advantages are presented in the table below (Table 7).

Table 7: Advantages of this article over research conducted in the years 2023 to 2025

Aspect	This article (2025)	Previous Research (2023–2025)	Advantage / Novelty
Focus	Synthetic text-based simulation combining cognitive-affective modeling with linguistic analysis	Mostly multimodal (speech, motion), large language models, user behavior simulation, or system prototyping	Uniquely integrates cognitive-affective and linguistic dimensions explicitly in a fully synthetic text dataset
Data Generation	Custom-built synthetic dataset of 27 sentences modeling emotional	Mostly based on existing corpora, real user data, or multimodal sensors	Enables controlled, repeatable experiments free from noisy real data; better for isolating

Aspect	**This article (2025)**	**Previous Research (2023–2025)**	**Advantage / Novelty**
	and cognitive HCI interactions		emotional-cognitive factors
Methodology	Hybrid symbolic-statistical approach embedding sentiment, subjectivity, POS distribution, and semantic similarity	Varies: from emotional LLM integration to multimodal interaction and behavioral models	Combines emotional polarity, linguistic structure, and semantic similarity in a single mathematical model
Emotional Analysis	Polarity and subjectivity quantified per sentence using TextBlob	Emotion recognition often integrated into LLMs or multimodal systems	Explicit modeling of emotional tone per sentence with clear formulaic representation for simulation purposes
Linguistic Analysis	Word count, average word length, POS distribution analyzed for syntactic and semantic depth	Often focuses on language generation realism or user simulation behaviors	Deep linguistic feature analysis to simulate and assess structural language properties in HCI text interactions
Semantic Similarity	TF-IDF + cosine similarity with heatmap visualization of sentence pairwise relationships	Some use semantic similarity in IR evaluation or language generation	Visual and quantitative exploration of sentence thematic clusters within the synthetic HCI text dataset
Simulation Scope	Text-based HCI simulation emphasizing cognitive-affective architectures and NLP interfaces	Often includes multimodal input/output (speech, gesture) or focuses on system-level prototyping	Focuses uniquely on text-only natural language interfaces with affective and cognitive modeling

Aspect	This article (2025)	Previous Research (2023–2025)	Advantage / Novelty
Results and Evaluation	Detailed per-sentence emotional and linguistic profiling, heatmaps for semantic coherence, and summary conclusions	Emphasis on system performance, interaction realism, or evaluation metrics in recommender and WoZ systems	Granular, interpretable insights into emotional and linguistic interplay at the sentence level in simulated HCI
Relevance to Training & Design	Provides a mathematically grounded framework for simulating HCI that can support cognitive-affective system design	Training scenarios and design processes addressed in some related works	Bridges theoretical modeling with practical simulation for system design and adaptive HCI applications

This article stands out by creating a controlled synthetic textual environment that blends emotional (affective) and linguistic (cognitive) features into a single, interpretable framework for human-computer interaction simulation. Unlike prior work that relies on multimodal inputs or large datasets from real users, approach of this article offers fine-grained, mathematically modeled insights into the emotional and syntactic aspects of language, advancing both the methodology and evaluation of text-based HCI systems. This emphasis on textual emotional and linguistic simulation with visualizations (heatmaps, charts) and a clear mathematical foundation gives this study a distinctive edge for researchers interested in natural language interfaces, cognitive-affective computing, and simulated user modeling.

5. Conclusion

This study proposed and implemented a hybrid text-based simulation framework for human-computer interaction (HCI) that combines cognitive-affective architectures with natural language interfaces. Through the synthetic generation and analysis of 27 pseudo-realistic interaction sentences, the model demonstrated its ability to integrate emotional polarity, subjectivity, linguistic features, and semantic similarity into a unified interpretation pipeline. The findings confirm that such simulations can meaningfully reflect the nuances of human expression, enabling intelligent systems to analyze, adapt to, and replicate humanlike responses. The use of both symbolic and statistical techniques allows for a layered understanding of affective and linguistic signals, offering a valuable alternative to data-hungry deep learning approaches. The evaluation of recent research (2023–2025) further validates the relevance and timeliness of this study. Compared to state-of-the-art methods, this work contributes a minimal-data yet insight-rich methodology suitable for both prototyping and educational settings. In essence, this work advances the simulation of HCI beyond surface-level pattern recognition, offering a cognitively and emotionally aware framework that paves the way for more humanlike, adaptive interfaces.

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