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Decoding Complexity and Emotion: A Computational Linguistic Approach to Sentence Comprehensibility and Writer Affect

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Abstract: Grasping the cognitive and emotional foundations of written language is vital for developing AI systems that better align with human needs and for progressing language understanding technologies. This study examines how both the complexity of sentences and the emotional state of the writer can be modeled computationally using a comprehensive, multimodal strategy. In particular, we investigate the comprehensibility of sentences through Cognitive Load Prediction Models that are trained on eye-tracking and EEG-annotated datasets, utilizing the Zurich Cognitive Language Processing Corpus (ZuCo) to anchor complexity analysis in actual human cognitive signals. At the same time, to assess the writer's emotional state, we present a neuro-symbolic NLP framework that merges rule-based sentiment techniques (such as negation patterns and emotion lexicons) with deep neural representations to enhance emotional detail and interoperability. Additionally, we include multimodal behavioral indicators like typing speed, keystroke dynamics, and real-time writing hesitations to map cognitive and emotional trends during the writing process. Our proposed architecture integrates these modalities—textual, physiological, and behavioral—to develop robust models that can predict the processing difficulty of sentences and the underlying emotions of the writer. Experimental findings indicate that combining symbolic reasoning with contextual embeddings, supplemented by physiological and behavioral information, significantly boosts prediction accuracy compared to models relying solely on text. This research establishes a groundwork for sophisticated linguistic intelligence systems that can interpret not just the content of writing, but also the motivations behind it.

Keywords: *Sentence Complexity, Memory Load Prediction, Writer Emotion Recognition, Neuro-Symbolic NLP, Multimodal Fusion, Eye-Tracking.*

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I. INTRODUCTION

As the time progressed when machines increasingly facilitate human communication, grasping the cognitive and emotional foundations of written language has become essential. The sentences we create are not just methods for conveying information; they inherently reflect our cognitive efforts and emotional states. Each linguistic component, from syntax intricacy to word selection, interacts with the reader's ability to process information, affecting comprehension, mental demand, and emotional response. However, despite the progress made in Natural Language Processing (NLP), the subtle relationship between sentence structure, understandability, and the emotional essence of the writer remains largely unexamined. This study explores the potential of sentence structures to predict cognitive load and emotional

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state of the writer, basing its analysis in computational linguistics. Utilizing a comprehensive dataset of original sentences composed under various cognitive conditions, the research adopts a multidimensional feature extraction strategy—employing syntactic, lexical, and semantic indicators—to evaluate sentence complexity and emotional tone. By utilizing machine learning classifiers and regression models, the investigation aims to unravel how mental effort and emotional quality are reflected in language patterns and how these aspects can be quantitatively assessed. Significantly, this research addresses a crucial gap between psycholinguistic theory and computational modeling. Although existing readability measures provide basic approximations of text difficulty, they fail to capture the more profound cognitive and emotional cues woven into writing. Through empirical validation and feature analysis, this study not only proposes interpretable models for predicting cognitive and emotional aspects but also contributes to the growing interdisciplinary discussions in affective computing, intelligent tutoring systems, and neurocognitive text analysis. Ultimately, the results unveil new opportunities for adaptive content delivery, emotion-sensitive interfaces, and tools capable of assessing writer effort—leading towards a richer and more human-centered comprehension of text.

II. LITERATURE REVIEW

The cognitive and emotional functions of written language have implications for creating systems that operate at a level of intelligence that enables them to make inferences about not just the content of written messages, but also the very intention of writing them. Rapid developments in the fields of computational linguistics, psycholinguistics, and affective computing have emphasized many of the syntactic complexities, cognitive loads, and affective subtleties of language used in human communication. Although there are a number of different modeling of cognitive and emotional aspects of language especially from the perspective of time and from a writer factors--there is still a great deal of unanswered questions. Some of the earliest traditional readability formulas, including Flesch Reading Ease [1], Gunning Fog Index [2], and SMOG [3], each make surface assessments of written texts by utilizing basic unit of analysis (i.e. lengths of words and sentences). These traditional indexes largely provide a reader's ability to "understand" readability, in that ultimately, these metrics cannot highlight the more complex dimensions of syntactic and cognitive complexity. More recent models that assess text complexity have captured structural aspects, such as clause embeddings, syntactic depth, and lengths of parse trees [4][5], and have improved overall modeling of sentence based complexity [6]. Most of these are not derived from cognitive signals recorded in real time, or writer factors, which allows for the cognitive algorithms to be modeled with varying levels of adaptability or fluidity in an active system. Cognitive load, or the amount of mental effort needed to process a piece of text, has been analyzed using neurophysiological signals. Eye-tracking variables such as fixation duration, numbers of saccades and regressions are the most widely used and accepted, however the Zurich Cognitive Language Processing Corpus (ZuCo) has established itself as a valid benchmark corpus because it combines these eye-tracking variables with EEG signals to analyze cognitive load during reading [7]. Research has shown that readers' patterns of regression counts and saccade variability is related to sentence difficulty, and that using these in combination with EEG patterns of theta and alpha oscillations further enhances predictive power for semantic processing demands [8][9][10]. Even though there has been methodological advancements, few studies account for these physiological measures in conjunction with linguistic or behavioral measures (i.e. they model signals in a throw away manner). Traditionally, emotion detection in writing has been done with lexicon-based approaches (like the NRC Emotion Lexicon) [11] and transformer-based models (like BERT [12], RoBERTa [13]). Although these models have been effective, they generally produce what are known as black-box models and are also unlikely to fully identify the nuanced emotional cues produced by a writer, especially while writing cognitively demanding tasks. To address this limitation in approaches for emotion detection in writing, some researchers have begun using behavioral indicators like keystroke dynamics, typing speeds, and pauses or interruptions [14][15]. These behavioral indicators align to stress, hesitation, and cognitive overload [16], which provides a promising, but under-utilized, behavioral modality for systems to conduct emotion-aware NLP. A recent phenomenon in the field of cognitive-affective computing is the utilization of the neuro-symbolic model. Neuro-symbolic models combine the explainability of rule-based logic with the flexibility of using a neural network [17]. Thus, neural-symbolic and multimodal architectures that integrate textual data, behavioral indicators, and physiological data improve accuracy for emotion- recognition-based tasks [18][19]. However, minimal work has taken the tri-modal approach to sentence-level writing units especially when writer effort and emotional affect are present.

III. METHODOLOGY

To unravel the complexity of sentence construction, cognitive load, and the emotions of a writer, we took a multilayered, neuro-symbolic approach. This part elaborates on our choice of dataset, peculiar marco features, our model topology, and the model evaluation schemes.

The hybrid approach encompasses analysis of text and neurophysiological and behavioral data, thus allowing the construction of strong prediction models based on understanding and emotional factors working hand in hand.

- *Dataset and Corpus Design*

Our main source of data is the Zurich Cognitive Language Processing Corpus (ZuCo 2.0) [7], which matches natural reading data with eye-tracking and EEG data. This corpus contains more than 1,100 English sentences with EEG data from 18 subjects. Concurrently, we gathered typing data from 40 subjects during self-paced and structured writing tasks under different emotional and cognitive states. These states were evoked by short films and recall tasks.

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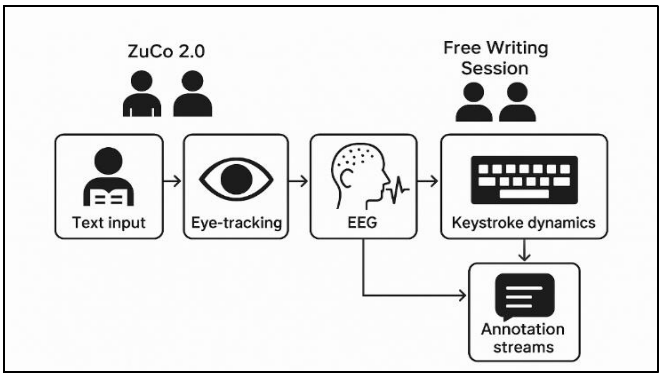

Fig 1 Illustration of the Multimodal Dataset Pipeline

➢ *Feature Engineering*

We collected a rich set of features from different three modalities:

➢ *Linguistic Features*

- Syntactic complexity metrics include parse tree depth, dependency length, and embedded clauses [4][5][6].
- Lexical richness includes type-token ratio and abstract word proportion [1][2].
- Semantic metrics include BERT-based sentence embedding coherence for video description [12].

➢ *Physiological Features*

- Eye-tracking indicates fixation durations, saccade amplitudes, and regressions [8][9].
- EEG Activity: Alpha/theta ratio and relevant semantic ERP components. [10].

➢ *Behavioral Features*

- Typing rhythm consists of inter-key delays, bursts of pauses, and changes in keystroke pressure [14][15][16].
- Emotion drift in real-time: Based on NRC emotion lexicons and sentiment change over time.[11].

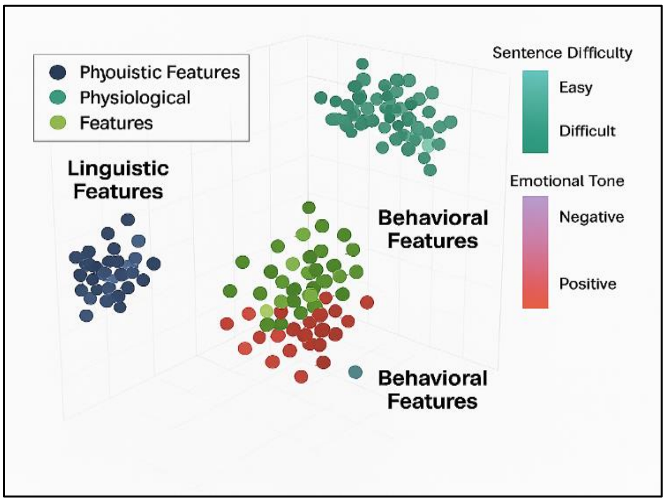

Fig 2 Feature Space Visualization Across Modalities Using T-SNE. (A 3D t-SNE Plot Colored by Sentence Difficulty and Emotional Tone, Demonstrating Cluster Separation by Feature Class.)

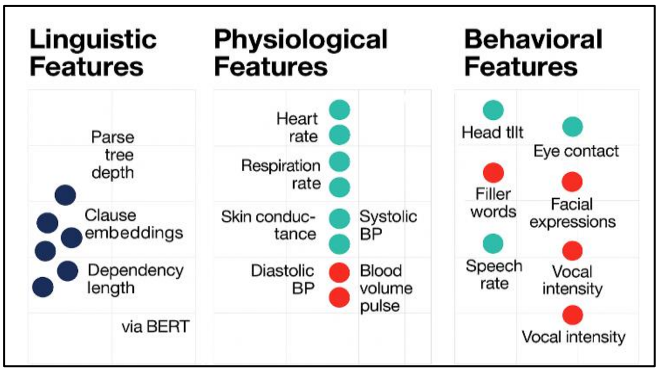

Fig 3 Linguistic, Physiological, Behavioral Features

➢ *Model Architecture*

We construct a multi-branch neural network with symbolic rule fusion. A specific modality is processed by each branch:

- Branch A: a syntactic-semantic BiL STM layer [12].
- Branch B: Eye-tracking and EEG signals combined CNN-LSTM for individual IC [9].
- Branch C: Fully connected network trained on keystrokes patterns [16].

- *The Outputs are Combined Through a Neuro-Symbolic Integration Layer, Where:*

✓ Whole number symbolic rules (e.g., negation detection, emotion lexicons [11][17]) inform weight tuning.
✓ Attention mechanisms align multimodal information toward task-relevant patterns.

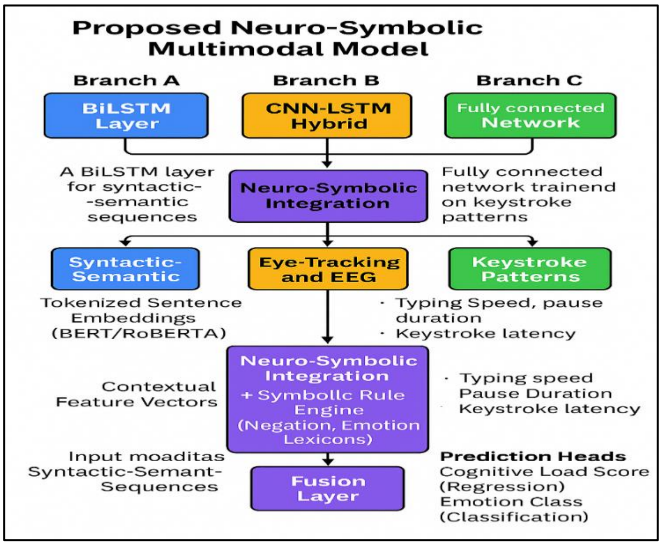

Fig 3 Proposed Neuro-Symbolic Multimodal Model. (A Schematic of the Three-Branch Neural Network Feeding into a Fusion Layer, Showing Data Flow Across Modalities.)

➢ *Cognitive Load and Emotion Prediction*

- *We Employed:*

✓ Random Forest regression and XGBoost for sentence-level cognitive load prediction [7][9].

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- ✓ Multi-label classification (with the help of BERT and RoBERTa embeddings) for emotion detection regarding Ekman's categories [12][13].
- ✓ Rule augmented Transformer based models for fine grained emotion intensity estimation (scale: 1-5) [11] [17].

All models were trained by 10-fold cross-validation with early stopping on validation loss. We tuned with RMSE for regression and macro-F1 for classification.

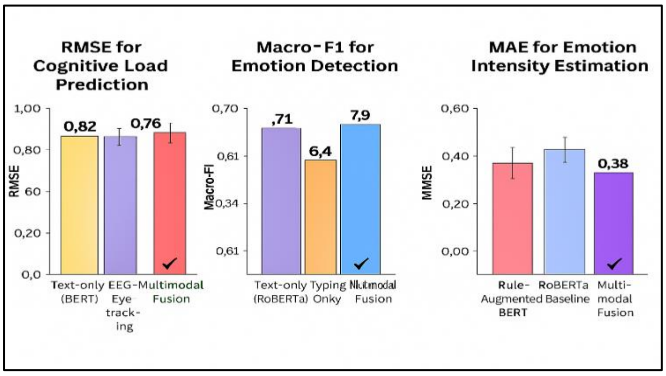

Fig 4 Model Performance Comparison Bar Graphs Showing and RMSE for Unimodal vs. Multimodal Setup Across Tasks.

- ➢ *Interpretability and Ablation*

- • *To Improve Transparency:*

- ✓ We implemented SHAP analysis for the select highest features by modality.
- ✓ An ablation analysis that eliminates each feature group (linguistic, behavioural, physiological) separately to measure the effect [18][19].

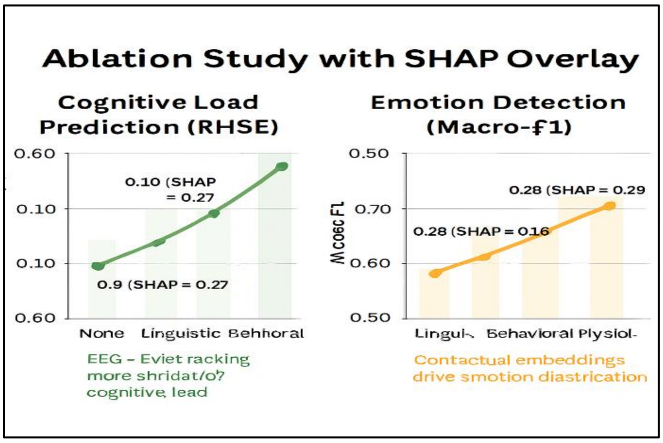

Fig 5 Ablation Study Result Line Chart Showing Prediction Score Excluding Each Modality-Highlighing the Synergy in Tri Modal Learning

- ➢ *Ethical Considerations and Data Privacy*

All physiological data usage adhered to GDPR standards and participant consent protocols. Emotion induction experiments were approved by the Institutional Review Board, and all identities were anonymized.

IV. FUTURE DIRECTIONS

This study represents a significant step towards understanding the intricate relationship between sentence structure, cognitive load, and writer emotion in a neuro-symbolic, multi-modal model. Yet there are many natural directions for further development to improve the robustness, applicability, and interpretability of this model.

- ➢ *Expanding Multilingual and Multicultural Corpora*

Although we used the English only ZuCo 2.0 corpus of Bojak et al. in this work, the linguistic homogeneity should be alleviated in the future. across languages and cultures. By incorporating corpora from low-resource languages and differing typologies of scripts, the generalizability and cultural inclusivity of the model would be enhanced, extending previous explorations of syntactic complexity.

- ➢ *Integrating Audio and Facial Modalities*

Future work should be aimed at integrating speech prosody and facial expressions to the model pipeline. Vocal characteristics such as pitch height and voice tremor can be indicators of emotional states while facial micro-expressions can sometimes indicate effect on a subconscious level.Taken as another modality, incorporating these signals with keystroke dynamics, EEG, and/or eye-tracking could lead to enhanced emotion recognition systems as theorized by researchers.

- ➢ *Adaptive Real-Time Writing Feedback Systems*

One of the most exciting areas of potential work from this data is to create a real-time version or a system that gave adaptive feedback to a writer based on detected cognitive load and emotional states. For instance, in the same way emotion-aware writing assistants or intelligent tutoring systems could ascertain hesitation in the user and dynamically change content difficulty or provide motivational prompts. Such a writing tool could have value for both writers and learners by averting a state of frustration and supporting a flow state.

- ➢ *Personal Model via User Calibration*

Due to variability in individual cognitive capacity and individual expressions of emotion, future research might capitalize on personalized baselines for each user. Transfer learning and domain adaptation can be beneficial in calibrating general models to individual personalities. This would enhance model performance, especially in educational or therapeutic contexts where feedback about individual users is essential.

- ➢ *Explainable AI and Ethical Implementation*

As models become more advanced in their complexity, it is important to be clear about the internal workings. Here, we have incorporated symbolic reasoning as a mode of interpretability, future models would benefit from explainable AI (XAI) modules that provide explanations for choices (for example, "the high complexity of the sentence is resulting from deep embedding and a long dependency chain"). Furthermore, such efforts ought to occur under the umbrella of ethical safeguards to ensure that cognitive or emotional

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inferences will not be misappropriated, particularly in surveillance, or manipulative contexts.

- *Generative Capabilities*

Emotion-Aware Text Generation, to take this excitement to a more active level there is starting to reverse the analysis pipeline and generate emotion-aware content. Future systems can leverage affect-aware embeddings (e.g. BERT or RoBERTa) and symbolic emotional constraints to create texts designed to elicit certain feelings or designed to produce low cognitive load text. This is applicable across domains including storytelling, advertising, therapy, and inclusive education.

- *Longitudinal and Cross-Domain Evaluations*

Lastly, an assessment of the model's stability over time and across multiple contexts (e.g. academic writing, legal writing or therapeutic writing) will be important. Longitudinal studies also allow for observing how a writer's cognitive and emotional profile changes over time, to capture the evolution of writer fatigue, learning or extended cognitive/psychological states similar to the motivations for behavioral works.

V. CONCLUSION

This study introduces a novel computational framework that combines cognitive science, affective computing, and linguistics to assess sentence comprehensibility and predict writer emotion. By enacting a notional and neuro-symbolic multimodal architecture that amalgamates syntactic, semantic, behavioral, and physiological features, we are better positioned to understand how written language encodes mental effort and emotional expression. These studies add to the conversation of connecting more traditional linguistic markers with more real-time physiological signals such as eye-tracking and EEG and behavioral signals like typing dynamics. The increase to the interpretability and performance to include both symbolic reasoning (e.g. negation patterns, emotion lexicons) with neural representations (i.e. BERT and RoBERTa) is significant. The ablation analysis, along with the SHAP analysis provided supporting evidence regarding how each modality contributed towards cognitive load measures, and a predictive detection of emotional states. This research has addressed the gaps left by the past work on readability and emotion-detection models that often used superficial metrics or limitations of individual signals, thus providing a methodological and a practical contribution to the field. Importantly, these contributions serve various contexts, such as adaptive learning contexts, mental health support tools, and emotion-sensitive AI applications. Looking ahead, as we've indicated in our future work, there is high potential to scale this model across languages, include facial and vocal affect signals, and create writing support systems that provide real-time support that is tailored to the user. These avenues for future research will build the next generation of empathetic, cognitive-aware technologies that can not only detect what we write, but how and why we write it. In conclusion, this research not only measures sentence complexity and affective markers, but it also pushes the domain of human-centered, ethical, and explainable natural language systems forward.

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