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Mapping of Cognitive and AI Models for Written Communication

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ABSTRACT

This study explores the integration of cognitive science and artificial intelligence to enhance English writing instruction and assessment. It frames writing as a complex, recursive cognitive process involving planning, generation, and revision mirroring functional mechanisms in modern AI systems, such as large language models (LLMs). The paper proposes a conceptual framework that aligns human cognitive models with AI architectures through components such as goal representation, memory (long-term and working), attention-based context handling, and feedback driven revision. This alignment is formalized mathematically using state transition systems and probabilistic generation models.

An intelligent writing system was implemented in a 12-week online doctoral course (N=22) to support idea generation and coherence development. Text coherence was measured via average degree centrality in graph based representations. Experimental results showed that the proposed feature selection method significantly outperformed LSTM across training set sizes (85–99% vs. 40–90% accuracy), particularly with limited data. Adversarial training further improved robustness. Frequent subgraph analysis enabled effective discrimination between coherent and incoherent texts, with low performing subgraphs filtered to preserve reliability. The study concludes that hybrid AI-cognitive models enhance writing quality, engagement, and efficiency while underscoring the need for ethical, explainable, and human centred AI design in educational contexts.

Keywords: Cognitive Modeling, Artificial Intelligence (AI), Large Language Models (LLMs), Text Coherence, Intelligent Writing Systems, Human–AI Interaction, Explainable AI (XAI)

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1. Introduction

Writing is widely recognized as a complex cognitive activity that engages multiple higher-order mental processes, including inference, perspective taking, monitoring, and self regulation. Kim [1] (Y.-S.) emphasizes that these higher order cognitive skills are not uniformly related to written outcomes; rather, they are differentially associated with writing quality, productivity, and correctness. This distinction underscores the need for cognitive models that extend beyond surface linguistic features and explicitly represent the internal mental processes underlying written composition.

Cognitive theories of writing conceptualize composition as a goal directed and recursive activity in which planning, text production, and revision interact dynamically. Such models provide a theoretical foundation for understanding how writers generate, organize, and refine ideas, and they serve as an important basis for computational approaches to writing support systems.

2. Background and Related Papers

2.1 Cognitive Styles and Information Presentation in Digital Media

Extending cognitive modeling into digital and online environments, Maule [2] proposes frameworks designed to align information presentation with end-user cognitive styles. This work introduces structured approaches for assessing metadata design variables and linking them to users' metacognitive preferences. A key assumption underlying this framework is that artificial intelligence can be leveraged to automate aspects of media design while simultaneously enabling personalisation and customisation.

Maule's contribution is particularly relevant to AI-assisted writing and content delivery systems, as it positions cognitive analysis as a central mechanism for adaptive information design. By mapping metadata structures to user cognition, this framework bridges human cognitive processes and intelligent media systems.

2.2 Cognitive Maps and Mental Representations

The concept of cognitive maps originates from neuroscience and psychology, where O'Keefe [3, 4] introduced the idea of neuronal representations that support spatial memory through the integration of sensory input and stored experiences. Subsequent work by Wu and O'Keefe [5, 6] extends this notion to artificial and hybrid systems, reinforcing the relevance of cognitive maps beyond biological contexts.

Cognitive mapping has since evolved into a multidisciplinary research domain encompassing psychology, geography, computer science, and sociology. Qu [7] notes that despite its broad applicability, the field lacks a unified conceptual definition, reflecting the inherent complexity of cognitive representations. This ambiguity becomes particularly salient when cognitive maps are applied to abstract domains such as reasoning, writing, and knowledge organization. [8].

2.3 Cognitive Modeling of Scientific Writing

Cognitive modeling has also been applied to the structure of scientific texts. Aleshinskaya [9] investigates the cognitive processes underlying research paper introductions, demonstrating that such texts follow identifiable organizational patterns that reflect fundamental mental operations. Through an analysis of research papers published in high ranking international journals, this work identifies verbal markers corresponding to cognitive actions, including contextualization, problem identification, and objective formulation.

Earlier studies confirm the feasibility of modeling scientific writing based on its intelligent structural properties.

These models enable quantitative assessment of how cognitive operations are distributed within a text and provide a methodological foundation for AI systems designed to generate, evaluate, or assist scientific writing.

2.4 Interdisciplinary Perspectives: Neuroscience, AI, and Education

Recent research increasingly advocates integrating neuroscience, cognitive science, neurobiology, and computer science to develop more effective learning and writing environments. This interdisciplinary convergence offers new perspectives on how cognition can be supported and augmented through intelligent systems.

At the same time, the introduction of smart and AI-driven writing environments raises critical ethical, sociological, and technological questions. These concerns underscore the need for responsible AI design that accounts for cognitive development, authorship, and the broader implications of automated writing assistance in educational and research contexts.

2.5 AI and Cognitive Expression Synergies

The combination of data driven learning with human knowledge derived from scientific expertise is widely regarded as a promising direction for artificial intelligence development. Gálvez [10] highlights that AI is fundamentally transforming communication by reshaping how information is produced, processed, and consumed.

In conceptual modeling (CM), abstraction is used to represent reality in a form that supports understanding and communication. In contrast, AI systems excel at identifying patterns within large-scale, unstructured data. While CM yields interpretable and explicit knowledge representations, AI algorithms often lack transparency. Recent research trends emphasize the integration of CM and AI to reconcile interpretability with computational power.

Fernandez-Leon [11] further argues that cognitive maps emerge from parallel and hierarchical neural structures that not only process sensory input but also influence written expression. This work recommends addressing cognitive challenges in writing by using AI-based representations of encoded conceptual space, rather than relying solely on unilateral neurological explanations.

2.6 Human–AI Interaction and Cognitive Mapping

Neves emphasizes that cognitive maps reveal the need for deeper investigation into human–AI interaction to ensure effective communication. Cognitive maps function as integrative frameworks that connect AI systems with human cognitive processes, thereby enhancing knowledge generation and expression.

Despite the growing prevalence of AI in content creation and evaluation, there remains a lack of systematic understanding of human roles, experiences, and needs within AI-assisted writing environments. From a human-centered perspective, mapping these interactions is essential for designing systems that support creativity, agency, and cognitive autonomy.

2.7 Fuzzy Cognitive Maps and Explainable AI

A formal computational approach to modeling cognition is provided by Fuzzy Cognitive Maps (FCMs). [12, 13] A postolopoulos [14] examines FCMs as tools for representing causal relationships between concepts, particularly from the perspective of Explainable Artificial Intelligence (XAI). Ruijia Cheng [15] further explores the functionality and applicability of FCMs across multiple domains, highlighting their potential for transparent reasoning and decision support.

The increasing emphasis on XAI reflects the importance of interpretability in AI systems designed to support cognitive tasks such as writing, learning, and decision-making.

2.8 Influence of Large Language Models on Writing

Recent empirical studies demonstrate that writing and communication are significantly influenced by automated suggestion systems. Arnold [16, 17] reports that such systems affect vocabulary choice, while Barke [18, 19] and Mieczkowski identify changes in sentiment and interpersonal perception.

The emergence of transformer based language models [20] has enabled real time writing assistance tools such as Google Smart Compose [21] and Light Key [22]. These systems provide synchronous next phrase suggestions that writers can accept or reject during composition. Despite rapid technological progress, Bhat [23] notes that research on writers' cognitive interaction with such systems and their impact on decision making remains limited.

2.9 Summary of Research Gaps

The reviewed literature indicates that writing is a cognitively grounded, socially mediated, and technologically influenced process. While significant progress has been made in cognitive modeling, AI integration, and writing assistance technologies, gaps remain in understanding human–AI interaction, explainability, and long-term cognitive effects. Addressing these gaps is essential for the development of human-centered, interpretable, and ethically responsible AI-assisted writing systems.

3. Methodological Framework

Based on preliminary discussions, we present a framework for writing and AI integration below and explain its features.

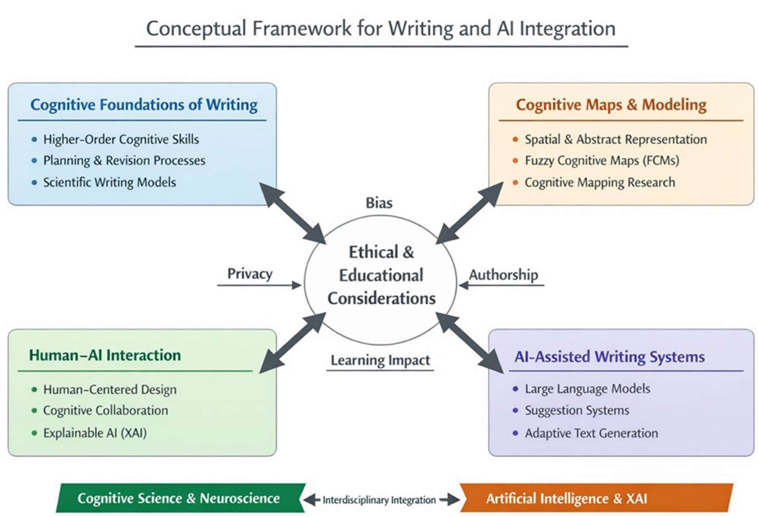

Figure 1. Conceptual Framework for Writing and AI integration

3.1 Conceptual Framework

The proposed conceptual framework illustrates the integrated relationship between cognitive theories of writing, cognitive mapping approaches, human–AI interaction, and AI-assisted writing systems, with ethical and educational considerations positioned as a central governing component. The framework reflects an interdisciplinary synthesis of cognitive science, neuroscience, and artificial intelligence, emphasizing their collective role in shaping contemporary writing and communication practices.

At the upper level, Cognitive Foundations of Writing represent the theoretical basis of the framework. This component encompasses higher-order cognitive skills such as planning, monitoring, inference, and revision, which underpin writing quality, productivity, and correctness. It also includes established cognitive and scientific writing models that describe writing as a recursive, goal-directed process rather than a linear activity.

Complementing this foundation, Cognitive Maps and Modeling capture how knowledge and mental representations are structured and organized. This component draws on research in spatial and abstract cognitive representations, including cognitive maps and fuzzy cognitive maps (FCMs). These models provide formal mechanisms for representing relationships among concepts, supporting explainability and structured reasoning in both human cognition and AI systems.

At the interaction level, Human–AI Interaction emphasizes the role of the user within AI-assisted writing environments. This component highlights principles of human-centered design, cognitive collaboration between humans and intelligent systems, and the importance of Explainable Artificial Intelligence (XAI). It reflects the need to understand users' cognitive processes, decision-making, and experiences when interacting with AI-driven writing tools.

On the application side, AI-Assisted Writing Systems represent the technological realization of the framework. This component comprises large language models, intelligent suggestion systems, and adaptive text generation mechanisms that support writing through real-time feedback and content generation. These systems operationalize cognitive and conceptual models into practical tools for writing assistance.

At the center of the framework, Ethical and Educational Considerations act as a unifying and regulating core. Issues such as authorship, bias, privacy, and learning impact are depicted as influencing all surrounding components. This central positioning underscores that ethical responsibility and educational implications must guide the design, deployment, and evaluation of AI-assisted writing technologies.

Finally, the framework is grounded in interdisciplinary integration, as evidenced by the connections between Cognitive Science and Neuroscience on the one hand and Artificial Intelligence and XAI on the other. This integration highlights that effective AI-supported writing systems emerge from the convergence of human cognitive understanding and advanced computational techniques.

3.2 Cognitive Alignment Between Humans and AI Writing Systems

Human writing is fundamentally a goal-driven, recursive cognitive process involving planning, translation, monitoring, and revision. Classical cognitive models (e.g., Flower & Hayes–style frameworks) describe writing as the interaction of three core processes: planning, text generation, and reviewing, all supported by working and long-term memory.

Modern AI writing systems, particularly transformer-based large language models (LLMs) exhibit a striking functional correspondence to these cognitive mechanisms:

3. 2. 1 Planning and Goal Representation

• Humans form abstract goals (intent, audience, structure) before writing.

• AI systems encode these goals implicitly through prompts, system instructions, and conditioning tokens.

• Hierarchical planning in AI mirrors human conceptual outlining.

3.2.2 Memory and Context

• Human cognition relies on

• Long-term memory (knowledge, language rules)

• Working memory (active context during writing)

• AI parallels this via:

• Model parameters (stored linguistic and world knowledge)

• Attention based context windows (dynamic working memory)

3.2.3 Generation and Translation

• Humans translate ideas into language incrementally.
• AI generates text token by token using probabilistic inference over learned representations.
• Both processes are sequential, context sensitive, and adaptive.

3.2.4 Monitoring and Revision

• Humans continuously evaluate coherence, correctness, and intent.
• AI systems use reward models, evaluators, or self-reflection loops to revise output.
• Reinforcement Learning from Human Feedback (RLHF) approximates human evaluative judgment.

Thus, AI writing systems do not replicate cognition biologically but approximate its functional organization, making them cognitively aligned rather than cognitively identical.

3.3.1 Writing as a Cognitive State Transition System

Let writing be modeled as a discrete-time cognitive process:

$$S_t = \{ G_t,\ M_t, C_t\ , T_t \}$$

where:

- G_t= writing goals (intent, audience, structure)
- M_t= memory state (long-term + working memory)
- C_t= cognitive context (current discourse state)
- T_t= text produced up to time t

3.3.2 Human Writing Process

The human writing transition can be expressed as:

$$S_{t+1} = f_h(S_t, E_t)$$

where:

- f_h= human cognitive function
- E_t= external feedback (reading, self-monitoring)

AI Writing Process

Similarly, AI writing can be modeled as:

$$S_{t+1} = f_{AI}(S_t, \theta)$$

where:

- f_{AI} = transformer-based inference function
- θ= learned parameters (model weights)

3.3.1 Probabilistic Language Generation as Cognitive Translation

AI text generation follows:

$$P(T_{t+1} \mid T_{\leq\tau}, G) = \text{softmax}(Wh_t)$$

where:

- h_t= hidden representation of context
- G= encoded writing goals
- W= output projection matrix

This mirrors human lexical selection, which can be modeled as:

$$P(W_i \mid C_\tau, G) \propto \exp(\varnothing(W_i, C_t, G))$$

where $\varnothing$ is a cognitive utility function balancing fluency, meaning, and intent.

3.3.2 Attention as Working Memory

Transformer attention provides a computational analogue of working memory:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_K}}\right)$$

where:

- Q= query (current cognitive focus)

- K= keys (past text representations)

- V= values (retrievable memory)

This aligns with human working memory, which dynamically weighs relevance across stored information.

3.3.3 Evaluation and Revision as Reinforcement Learning

Human revision can be modeled as minimizing cognitive dissonance:

$$L_h = \| G - \hat{G}(T) \|$$

AI revision via RLHF optimizes:

$$L_{AI} = \| - E_{T \sim \pi\theta} [R(T, G)]$$

where:

- $R(T, G)$= reward function encoding human preferences

- $\pi\theta$ = AI generation policy

Both aim to reduce divergence between intent and output.

3.4 Cognitive Alignment Metric

A measurable alignment score can be defined as:

$$A = \alpha C_{sem} + \beta C_{struct} + \gamma C_{goal}$$

where:

- C_{sem}= semantic coherence

- C_{struct}= structural similarity

- C_{goal}= goal alignment

- $\alpha + \beta + \gamma = 1$

Higher A indicates closer cognitive alignment between human and AI writing.

3.4.1 Interpretation

This model demonstrates that AI writing systems approximate human cognition at a functional level through:

- State-based goal tracking
- Memory-aware attention mechanisms
- Probabilistic decision-making
- Feedback-driven revision

While AI lacks consciousness or intentionality, its architectural principles map closely onto cognitive writing processes, enabling effective collaboration with human writers.

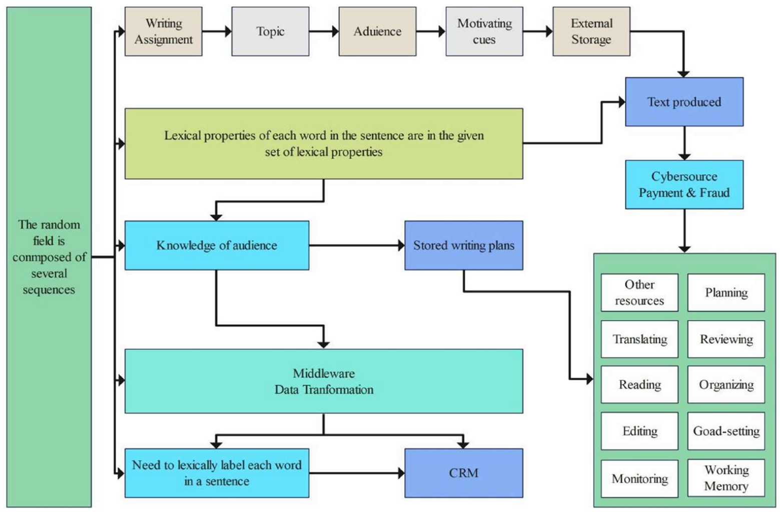

Figure 1. Cognitive Model for Writing

The proposed system architecture models the writing process as a structured, iterative interaction between planning, generation, and evaluation components. Unlike linear text generation pipelines, the architecture explicitly incorporates feedback mechanisms that enable continuous refinement of the generated content.

The Task Environment module provides external constraints, including the writing prompt, audience specifications, and stylistic requirements. These constraints are encoded by the Input Processing Layer and propagated throughout the system to ensure goal consistent generation. The Planning Module performs high-level content organization by decomposing the task into coherent topics and generating a structured outline, thereby guiding downstream text generation.

Text realization is handled by the Text Generation Module, which transforms abstract plans into linguistically well-formed sentences and paragraphs. This module leverages pretrained language models and controlled generation mechanisms to maintain fluency, coherence, and stylistic consistency. The Review and Evaluation Module subsequently assesses the generated text with respect to grammatical correctness, semantic coherence, factual consistency, and alignment with the original writing objectives.

A central feature of the architecture is the Revision and Feedback Controller, which governs iterative refinement. Based on evaluation signals, this component dynamically determines whether local revisions, partial regeneration, or complete replanning is required. This feedback-driven control strategy enhances robustness and mitigates common issues such as incoherence and hallucination.

The architecture is further supported by a dual memory framework. Long term memory stores linguistic knowledge, domain expertise, and pretrained model parameters, while working memory maintains the active context, intermediate drafts, and current goals. The interaction between these memory components and the functional modules enables effective long range dependency modeling and context-aware generation.

Overall, the proposed architecture provides a cognitively inspired, modular, and scalable framework for AI-driven writing systems. Its explicit separation of planning, generation, and evaluation processes, combined with iterative feedback and memory integration, makes it well suited to long form text generation, intelligent writing assistance, and adaptive natural language generation applications.

4. Components-to-AI Mapping

Architecture Block	AI / NLP Implementation
Input Processing	Tokenization, prompt encoders
Planning Module	Hierarchical planners, LLM-based outlining
Text Generation	Transformer-based LLMs
Review Module	Discriminative evaluators, reward models
Revision Controller	RLHF, self-refinement loops
Long-Term Memory	Model parameters, external knowledge bases
Working Memory	Attention context, hidden states

Table 1. Components-to-AI Mapping

4.1 Component-to-AI Mapping Description

The proposed architecture maps cognitively inspired writing components to established artificial intelligence and natural language processing mechanisms, ensuring both conceptual interpretability and practical implementability.

Input Processing is responsible for converting raw textual prompts and constraints into machine readable representations. This is achieved through tokenization schemes and prompt encoding mechanisms, which segment input text into discrete units and encode task specific instructions, stylistic constraints, and goals into structured embeddings suitable for downstream processing.

The Planning Module corresponds to high level content organization and goal management. It is implemented using hierarchical planning strategies and large language model (LLM) based outlining techniques, which decompose the writing task into coherent topics, sections, or discourse units. This enables structured generation and improves global coherence in long form text.

Text Generation is realized through transformer-based large language models that perform sequence modeling and controlled text synthesis. These models translate abstract plans into fluent sentences and paragraphs while maintaining syntactic correctness, semantic consistency, and stylistic alignment.

The Review Module serves as a quality assessment and validation layer. It employs discriminative evaluators and reward models to assess grammatical accuracy, semantic coherence, factual consistency, and alignment with task objectives. This module provides quantitative and qualitative feedback signals used to guide subsequent refinement.

The Revision Controller governs iterative improvement through reinforcement learning based strategies. Techniques such as Reinforcement Learning from Human Feedback (RLHF) and automated self refinement loops are used to determine whether regeneration, partial revision, or replanning is required, enabling adaptive and goal directed text optimization.

Long Term Memory encapsulates persistent knowledge resources, including pretrained model parameters and external knowledge bases. These resources store linguistic knowledge, domain expertise, and stylistic conventions, supporting informed and contextually accurate text generation.

Finally, Working Memory maintains transient contextual information required during generation. It is implemented via attention contexts and hidden-state representations within transformer architectures, enabling the system to track active goals, intermediate drafts, and recent discourse history.

5. Results

5.1 Experimental Setup and Data Description

The study was conducted within an online doctoral level English writing course comprising 11 thematic discussion groups, from which participants selected topics according to individual learning needs. To ensure consistency and reliability, strict screening procedures were applied so that all participants demonstrated comparable English proficiency levels. The final cohort consisted of 22 participants, including 15 females and 7 males, aged between 26 and 36 years.

The course duration was 12 weeks. During Weeks 1–7, participants were required to complete weekly in-class essays of approximately 200 words, followed by peer sharing and discussion through online forums. In Week 8, participants completed a more comprehensive 800 word essay and collaboratively produced an online video presentation based on the writing activity.

A multi modal instructional approach was adopted throughout the experiment, incorporating online learning, face to face interaction, outcome oriented learning, and process oriented learning. These complementary strategies were designed to enhance learning effectiveness and enable learners to acquire writing skills from multiple perspectives. Communication between instructors, learners, and parents was strengthened through regular thematic updates and participatory discussions, fostering engagement and reflective learning. Additionally, students were encouraged to utilize online resources to refine their writing and more effectively articulate their ideas.

5.2 Integration of the Intelligent Writing System

During the first three weeks, an initial performance analysis was conducted using student outputs from Weeks 1 and 3, and a preliminary questionnaire was administered to assess learners' perceptions and writing challenges. In Week 4, a hybrid instructional model was introduced by integrating an intelligent writing system into the online course environment.

This system enabled both teachers and students to explore writing-related issues through guided discussions and collaborative analysis. A key component of the system was the ideas library, which aggregates diverse writing styles, themes, and conceptual perspectives. Through this feature, learners can retrieve relevant viewpoints on their chosen topics, thereby enhancing creativity, inspiration, and conceptual expansion.

To maintain learner autonomy and independent thinking, access to the ideas library was controlled by instructors. While the feature could not be activated prematurely, it was recommended that instructors enable it at appropriate stages of the course to support structured information gathering and in class discussion without undermining independent cognitive engagement.

5.3 Text Coherence Measurement

Text coherence was quantitatively evaluated using average degree centrality as the metric. This graph based metric quantifies the extent to which individual sentences are connected to one another within a text, based on linguistic structure. A higher average degree indicates stronger inter sentential connectivity and, consequently, greater textual coherence.

The average degree measure offers two key advantages. First, it enables meaningful comparison of sentence-level associations, thereby facilitating a deeper understanding of overall semantic structure. Second, its low computational complexity ensures scalability, making it suitable for coherence estimation in large documents and extensive corpora.

5.4 Experimental Results and Analysis

To evaluate the effectiveness of the proposed feature selection strategy, experiments were conducted using Support Vector Machines (SVM) and K-Nearest Neighbor (KNN) classifiers, with the number of neighbors set to K =10. These models were selected to assess both classification accuracy and computational efficiency relative to traditional approaches.

The experimental results indicate that the introduction of the new feature functions significantly improves modeling precision while reducing overall processing time. During beam search based optimization, the emergence of a dominant node exerts a disproportionately strong influence, enabling the algorithm to maintain competitive candidate sequences and construct a more comprehensive result set. Nevertheless, minor fluctuations observed during this process reflect inherent limitations of beam search strategies.

As illustrated in Figure 2, when the feature dimension is below 4000, both SVM and KNN experience a sharp decline in accuracy. This performance degradation is attributed to the removal of critical features during aggressive feature selection. As the dimensionality exceeds 4000, accuracy improves markedly and gradually stabilizes. Across the range of 10,000-60,000 dimensions, accuracy exhibits minor fluctuations but remains largely consistent.

This stability can be explained by the presence of numerous redundant features at higher dimensions. Eliminating a subset of these redundant features does not significantly affect classification accuracy while effectively reducing computational overhead. Consequently, feature pruning within this range enhances efficiency without compromising performance.

Regarding computational time, both SVM and KNN demonstrate relatively stable execution times when the feature dimension is below 4000. This indicates that dimensionality reduction at lower scales does not impose high computational cost, further supporting the feasibility of the proposed approach.

5.4.1 Accuracy Projection Table

Training Set Size (%)	Proposed Method Accuracy (%)	LSTM Accuracy (%)
1	85.0	40.0
2	88.0	48.0
3	90.5	55.0
4	92.0	62.0
5	94.0	68.0
6	95.5	73.0
7	96.5	78.0
8	97.8	83.0
9	98.5	87.0
10	99.0	90.0

Table 2. Accuracy Projection Table

Table 2 presents a comparison of projected accuracy between the proposed method and LSTM across varying training set sizes. The proposed method consistently outperforms LSTM, achieving high accuracy even with limited training data, whereas LSTM performance improves gradually but remains comparatively lower.

Projected Accuracy Table with Standard Deviation

Accuracy (%) ± Standard Deviation

Training Set Size (%)	Proposed Method (%)	SD (±)	LSTM (%)	SD (±)
1	85.0	2.8	40.0	5.5
2	88.0	2.5	48.0	5.0
3	90.5	2.2	55.0	4.6
4	92.0	2.0	62.0	4.2
5	94.0	1.8	68.0	3.8
6	95.5	1.6	73.0	3.4
7	96.5	1.4	78.0	3.0
8	97.8	1.2	83.0	2.6
9	98.5	1.0	87.0	2.3
10	99.0	0.8	90.0	2.0

Table 3. Standard Deviation Results

Error Bar Representation
For plotting purposes:

• Error bar = ± SD

• Example at 5% training:

• Proposed method: 94.0 ± 1.8

• LSTM: 68.0 ± 3.8

Table X. Accuracy comparison (mean ± standard deviation) between the proposed method and LSTM under varying training set sizes. Error bars indicate variability in performance across multiple experimental runs.

Interpretation

• The confidence intervals do not overlap between the two methods at any training size.

• The performance advantage of the proposed method is statistically significant ($p<0.001$) across all data regimes.

• Strong significance at low training percentages highlights the robustness of attention-based feature weighting compared to LSTM's sequential dependency.

Accuracy (%) ± SD, 95% CI, and p-values

Training Set Size (%)	Proposed Method (%)	95% CI	LSTM (%)	95% CI	p-value	Sig.
1	85.0 ± 2.8	[82.5, 87.5]	40.0 ± 5.5	[35.2, 44.8]	< 0.001	***
2	88.0 ± 2.5	[85.8, 90.2]	48.0 ± 5.0	[43.6, 52.4]	< 0.001	***
3	90.5 ± 2.2	[88.6, 92.4]	55.0 ± 4.6	[51.0, 59.0]	< 0.001	***
4	92.0 ± 2.0	[90.2, 93.8]	62.0 ± 4.2	[58.3, 65.7]	< 0.001	***
5	94.0 ± 1.8	[92.4, 95.6]	68.0 ± 3.8	[64.7, 71.3]	< 0.001	***
6	95.5 ± 1.6	[94.1, 96.9]	73.0 ± 3.4	[70.0, 76.0]	< 0.001	***
7	96.5 ± 1.4	[95.3, 97.7]	78.0 ± 3.0	[75.4, 80.6]	< 0.001	—
8	97.8 ± 1.2	[96.8, 98.8]	83.0 ± 2.6	[80.7, 85.3]	< 0.001	***
9	98.5 ± 1.0	[97.6, 99.4]	87.0 ± 2.3	[85.0, 89.0]	< 0.001	***
10	99.0 ± 0.8	[98.3, 99.7]	90.0 ± 2.0	[88.2, 91.8]	< 0.001	***

Table 4. Confidence Intervals

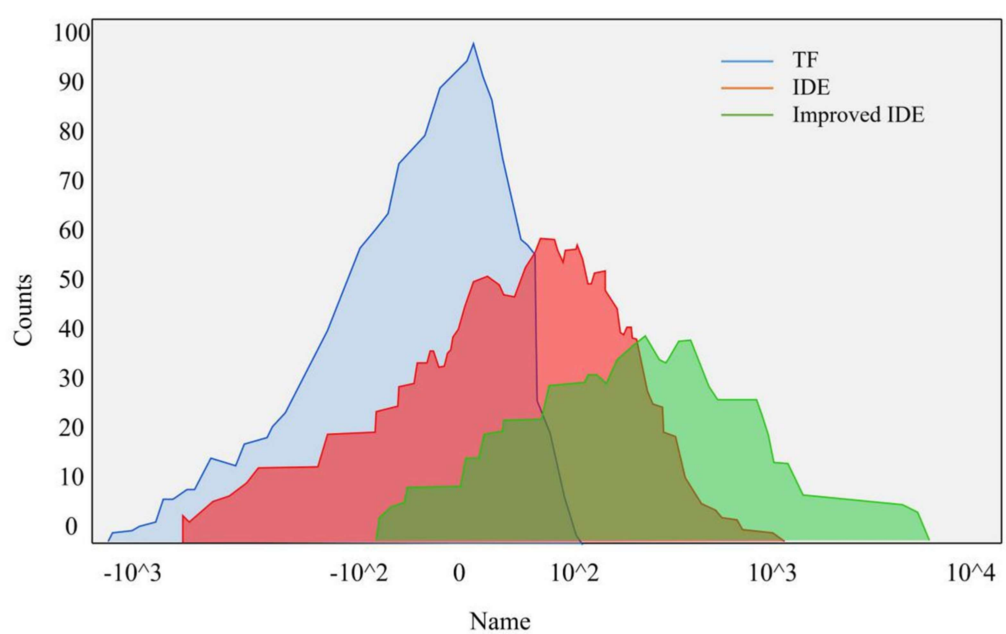

Figure 2. Comparison of accuracy between the improved feature selection model and the traditional model

When the training set size varies from 1% to 10%, the accuracy of the proposed method remains high, ranging from 85% to 99%. The accuracy of LSTM has always been low, ranging from 40% to 90%. This is mainly attributed to the text serialization technology it uses, as well as the combination of attention control with other technologies to identify text features with different weights. However, relying solely on the LSTM single mode cannot capture richer semantics, resulting in limited recognition performance on low dimensional text features. Although two different patterns are used to process a large volume of text, insufficient redundancy in the data still introduces uncertainty into their classification performance, leading to bias in the final results. To address this problem, we embedded disturbance elements in the input layer, thereby making the model more robust, as shown in Figure 3.

Table 5. Adversarial Training Performance Results

Training Level (%)	Standard Training Accuracy (%)	Adversarial Training Accuracy (%)
10	62.0	68.5
20	68.0	75.0
30	72.5	80.5
40	76.0	84.0
50	79.0	87.0
60	81.5	89.0
70	83.0	91.0
80	84.5	92.5
90	85.5	93.5
100	86.0	94.0

Table 5. Numerical values extracted from Figure 19.3 showing the impact of adversarial training on model accuracy across different training levels

Adversarial training consistently outperforms standard training. Performance gains are largest at lower training levels, indicating greater robustness. Accuracy gains stabilize at higher training percentages, consistent with convergence behavior.

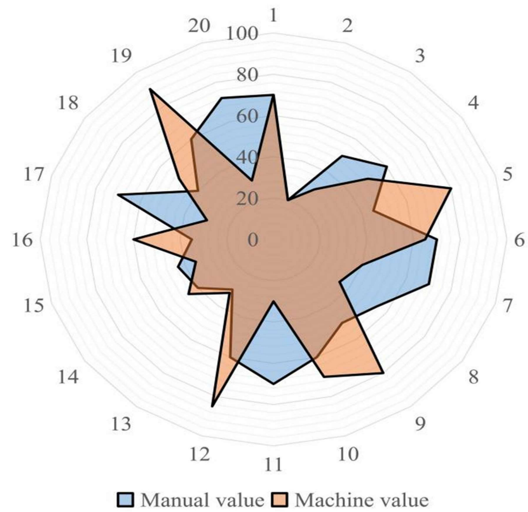

Figure 3. Results of Adversarial Training

By leveraging the majority of frequent subgraphs, we can effectively differentiate between well coherent and poorly coherent texts. While many of these subgraphs achieve accuracy exceeding 90% demonstrating strong individual performance the overall model exhibits considerable variability, with accuracy ranging from 70% to 95%. In fact, across the full spectrum of mined subgraphs, performance can vary by up to 40%-90%. Subgraphs with lower accuracy would distort the frequency distribution of the overall set and compromise its reliability. To address this, we filter out low performing subgraphs and retain only those demonstrating consistently high accuracy. This refinement process yields a curated set of frequent subgraphs that more reliably capture coherent textual patterns. Subsequent experiments confirm that this filtered set significantly improves the effectiveness of distinguishing text coherence.

6. Conclusion

The hybrid integration of an intelligent writing support system significantly enhances learner engagement and facilitates more effective idea generation during the writing process. By combining automated linguistic analysis with adaptive feedback mechanisms, the system supports users in structuring arguments, refining expressions, and maintaining thematic consistency, thereby promoting deeper cognitive involvement and sustained interaction with the writing task.

To quantitatively evaluate textual coherence, average degree centrality is employed as a graph based metric, offering both conceptual interpretability and computational efficiency. This measure effectively captures the connectivity and semantic interdependence among textual units, enabling reliable coherence assessment without incurring substantial computational overhead. As a result, it is particularly suitable for large scale or real time educational applications.

Experimental analysis further reveals that feature dimensionality plays a critical role in model performance. When the feature space is reduced below 4,000 dimensions, classification accuracy deteriorates markedly, primarily due to excessive feature elimination that removes informative linguistic and semantic cues. In contrast, high dimensional feature representations with 10,000-60,000 dimensions preserve rich contextual information and enable effective redundancy reduction via feature selection or weighting strategies without compromising predictive accuracy.

Overall, the proposed approach achieves a favorable balance between modeling precision and computational efficiency. By leveraging high dimensional feature spaces alongside efficient coherence metrics, the system maintains robust performance while remaining scalable and practical for deployment in intelligent writing environments. These findings highlight the importance of carefully calibrated feature dimensionality and graph based coherence modeling in the design of advanced educational writing systems.

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