Publication Date: 02 September 2026
Archs Sci. (2026) Volume 75, Issue 6 Pages 17-30, Paper ID 2025603.
https://doi.org/10.68304/as/75603

A Computational Model for Cultivating Innovative Ability in College English Based on Deep Learning and Combinatorial Mathematics

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Abstract In the context of AI-enabled education, College English teaching is gradually shifting from a predominantly knowledge-transmission model toward an approach that also emphasizes the cultivation of innovative language abilities. Nevertheless, innovative language production is structurally complex, dynamically evolving, and difficult to quantify in a transparent manner. Existing deep-learning approaches frequently concentrate on outcome prediction or text generation and provide only limited explicit modeling of learners' cognitive structures and the mechanisms through which innovative expressions are formed. To address these limitations, this paper proposes a computational modeling framework for innovation-oriented College English learning that integrates deep learning with combinatorial mathematics. First, a hierarchical Transformer-based semantic encoder maps discrete linguistic units into a continuous latent semantic embedding space, thereby providing a measurable semantic representation. Second, a cognitive-structure graph is constructed in which linguistic knowledge units are treated as nodes, and the innovation-oriented learning process is formalized as a structural mapping problem. Knowledge reorganization is then represented through combinatorial operations, including permutation, substitution, merging, and reconstruction. On this basis, a multi-objective optimization function that balances semantic novelty, semantic coherence, and structural complexity is formulated so that innovation generation can be treated as a computable combinatorial optimization problem. Approximate solutions are obtained using a genetic algorithm, beam search, and reinforcement learning. Systematic experiments are conducted on an authentic College English writing corpus. The reported results indicate that the proposed method outperforms the comparison methods with respect to innovation score, novelty distribution, structural controllability, and learning stability. Multidimensional visualization further supports the effectiveness of the framework in representing innovative ability, cognitive-structure evolution, and adaptation to individual differences.

Index Terms College English learning, innovative ability cultivation, deep learning, combinatorial mathematics, Transformer, semantic embedding, cognitive-structure modeling, educational intelligence

I. Introduction

With the rapid development of artificial intelligence (AI), the education sector is undergoing a substantial transition from conventional digitalization toward more intelligent and adaptive forms of teaching and learning [1]. In higher education in particular, the objectives of English learning have gradually expanded beyond the acquisition of linguistic knowledge to include comprehensive language competence, flexible reasoning, and innovative expression. In response to the practical demands of international academic communication, cross-cultural collaboration, and the preparation of globally oriented professionals, College English teaching requires not only linguistic accuracy but also the ability to formulate original expressions, reorganize viewpoints, and transfer meaning across complex contexts [2], [3]. Recent discussions of large language models and AI-supported education further illustrate both the opportunities and the pedagogical challenges associated with this transition [4]. Consequently, the effective cultivation and computational characterization of students' innovative abilities during English learning have become important research concerns in technology-enhanced higher education.

Innovative language production, however, is intrinsically complex and dynamic. Unlike tasks such as grammatical error correction or conventional writing-score prediction, innovative expression involves several interacting processes, including knowledge selection, semantic reorganization, structural transfer, and the progressive development of cognitive representations. These internal mechanisms are difficult to characterize adequately through conventional teaching models or simple statistical procedures [5], [6]. Existing College English evaluation systems frequently emphasize accuracy, test scores, or rule-based matching, whereas the assessment of innovative behavior often remains dependent on subjective judgment. As a result, the field still lacks a unified computational representation together with interpretable evaluation criteria for innovation-oriented language learning. This limitation becomes particularly important in AI-enabled educational environments, because intelligent systems require explicit and measurable representations if they are to support the cultivation rather than merely the assessment of innovative ability [7].

In recent years, deep learning has produced major advances in natural language processing. Transformer architectures and contextual language-representation models have achieved strong performance in machine translation, text generation, semantic representation, and a wide range of downstream language tasks [9], [10]. These developments, together with neural approaches used in educational applications [8], provide an important technical basis for intelligent language-learning systems. Methods for automated writing evaluation, grammatical feedback, pronunciation assessment, and adaptive learning support continue to emerge, and they can improve the efficiency and responsiveness of technology-assisted language instruction. Nevertheless, many existing methods still model learning primarily as a mapping from textual input to predicted output. Such approaches can be effective for prediction, but they often provide only limited access to the formation and evolution of a learner's internal knowledge structure. This lack of explicit structural representation makes it difficult to explain how innovative language abilities are generated, reorganized, and stabilized over time.

From a cognitive and representational perspective, language learning is not merely the accumulation of isolated information; it is also a process of structured knowledge construction. Vocabulary, formulaic expressions, syntactic patterns, and discourse-level relations are repeatedly activated, connected, reorganized, and transferred during learning, gradually forming an interconnected knowledge network. Graph-based knowledge representations provide a natural computational language for describing such entities and relations [11], while language-learning systems can supply task-specific evidence for how individual linguistic units are acquired and evaluated [12]. Innovative expressions may then be interpreted as new, semantically constrained combinations within this structured network. Accordingly, relying only on continuous semantic vectors, without an explicit account of structural relations, may obscure important characteristics of innovative behavior.

To address related limitations, previous studies have introduced knowledge graphs, concept networks, computational-thinking models, and cognitive diagnostic mechanisms to represent learning states. Such approaches improve structural interpretability because they make relationships among knowledge components explicit; however, they often depend on predefined rules, static relations, or task-specific diagnostic assumptions, which can make dynamic knowledge reorganization difficult to represent. At the same time, generative language models provide powerful expressive capabilities, yet generation is usually governed by learned probability distributions rather than by an explicit representation of the permissible innovation space, structural complexity, and semantic constraints. Without additional control mechanisms, generated structures may therefore exhibit semantic drift, unnecessary redundancy, or changes that are difficult to interpret pedagogically [13].

The evaluation of innovation-oriented learning also presents a substantial methodological challenge. Excessive novelty may produce semantic incoherence or structurally implausible expressions, whereas overly restrictive consistency requirements may suppress meaningful variation and creative reformulation. A useful computational framework must therefore balance novelty with semantic coherence and structural economy rather than maximizing any single criterion in isolation. Related work on deep-learning-supported educational practice demonstrates the value of multidimensional evaluation, although the appropriate balance among these dimensions remains task dependent [14], [15]. Establishing a measurable and optimizable framework for novelty, rationality, and structural complexity is therefore a central requirement of the present study.

From a computational perspective, innovation generation can be formulated as a large-scale search over discrete structures. Linguistic innovation is not treated here as an unconstrained perturbation in a continuous vector space; instead, it is represented through operations such as selecting, arranging, substituting, merging, and reconstructing discrete linguistic units. Continuous semantic representations remain important because they provide similarity and coherence information, but they do not by themselves specify which structural transformations are admissible. Existing deep-learning models generally optimize latent representations implicitly, and they do not always exploit combinatorial structure explicitly when defining the search space of possible innovative expressions.

Against this background, this paper proposes a computational model of innovation-oriented College English learning that integrates deep semantic modeling with combinatorial mathematics. The framework takes linguistic cognitive structure as its central representation, describes learning as the dynamic evolution of a semantic and relational structure, and connects continuous semantic embeddings with discrete structural transformations. In this way, the proposed approach establishes a unified computational pathway from semantic representation and cognitive-graph construction to constrained innovation generation and multi-objective optimization.

II. Mathematical Modeling of Cognitive Structure

A. Knowledge Structure Graph Model

To characterize cognitive structure formally during College English learning, this study adopts a computational modeling perspective and represents the language-knowledge system as a graph. Because English learning involves many discrete semantic units together with heterogeneous relations among them, graph-based representations are well suited to describing hierarchical organization, dependencies, and associations within linguistic knowledge [11], [16]. Figure 1 illustrates the proposed framework for representing both the overall English knowledge system and the learner's current cognitive state. The complete knowledge domain is abstracted as a directed graph $\mathcal{G} = (V, E)$, in which nodes denote minimal semantic or structural knowledge units and directed edges encode linguistic relations. The edge set may represent syntactic dependencies, semantic associations, and pragmatic-functional relations, thereby allowing several levels of language knowledge to be represented within a unified mathematical structure.

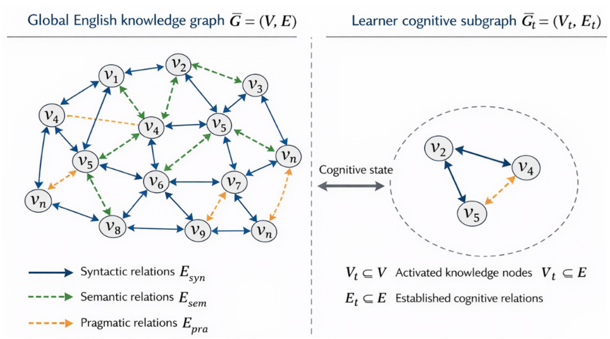

Figure 1: Graph-Based Representation of English Knowledge Structure and Learner Cognitive Subgraph

Therefore, this paper defines the complete English knowledge system as a directed graph, whose mathematical form is as follows:

$$\mathcal{G} = (V, E). \tag{1}$$

In this model, the node set $V = \{v_1, v_2, \ldots, v_n\}$ represents the basic semantic and structural units that constitute the modeled English knowledge system. Each node corresponds to a minimal learnable knowledge object, such as a lexical item, a fixed phrase, a syntactic template, or a pragmatic-functional pattern. The edge set $E \subseteq V \times V$ describes structural relationships among these units, while edge direction represents dependency or organizational relations from lower-level elements toward higher-level linguistic structures. The graph can therefore represent not only lexical co-occurrence and semantic association but also grammatical relations involving modification, nesting, subordination, and functional dependence. This formulation provides a common representational framework in which heterogeneous forms of language knowledge can be analyzed jointly.

Within this model, a learner is not assumed to have equal access to all knowledge nodes at a given stage of learning. Instead, only a subset of nodes and relations is considered active or reliably available. Accordingly, the learner's cognitive state at time t is represented as a subgraph of the complete knowledge graph, defined as follows:

$$G_t = (V_t, E_t), \quad V_t \subseteq V, \tag{2}$$

where V_t denotes the set of semantic units that the learner has mastered or can reliably invoke at time t, and E_t denotes the set of knowledge relations established among those units. The resulting subgraph represents the learner's current cognitive state: its size reflects knowledge coverage, whereas its topology reflects the organization and connectivity of the learner's linguistic knowledge. As learning progresses, the cognitive subgraph can evolve through the acquisition of new units, reinforcement of previously acquired knowledge, and reconstruction of relationships among existing units. Both node membership and connection patterns are therefore allowed to change over time.

To describe the availability of individual knowledge units more precisely, a node-activation function is introduced to quantify the learner's current state. For any semantic unit $v_i \in V$, its activation strength at time t is defined as:

$$a_t(v_i) \in [0, 1]. \tag{3}$$

This value characterizes the degree to which a knowledge unit is available to the learner. A lower activation value indicates that the unit has not yet formed a stable or readily accessible representation, whereas a higher value indicates that it can be invoked more reliably during language-comprehension and language-production tasks. The learner's effective cognitive node set at time t can therefore be defined by applying an activation threshold. This formulation supplements the discrete graph representation with a continuous state variable and makes changes in knowledge availability quantitatively expressible.

At the graph structure level, to characterize the complexity of the learner's language cognitive structure, this paper uses a structure density index to describe the cognitive subgraph, defined as follows:

$$\rho(G_t) = \frac{|E_t|}{|V_t|(|V_t| - 1)}. \tag{4}$$

For a directed graph without self-loops, this indicator measures the proportion of realized connections among all possible ordered node pairs. It therefore provides a compact description of the connectivity of the learner's represented knowledge structure. A higher density indicates that a larger proportion of potential relations among active language units has been established within the model. In the proposed framework, such connectivity is interpreted as supporting the integration of linguistic elements needed for understanding complex structures and constructing more varied expressions, although density is only one component of the overall cognitive representation.

From a dynamic perspective, learning can be viewed as the evolution of the cognitive graph over time. Under the combined influence of learning activities, feedback, and instructional intervention, a learner's state changes from G_t to G_{t+1}. This transition may involve node-set expansion, strengthening or weakening of activation values, and reconstruction of structural relations. Modeling these changes explicitly provides a natural interface for the subsequent integration of deep semantic representation and combinatorial optimization. The language-learning process can thus be expressed as a sequence of computable structural transformations rather than as a single static prediction task.

Within this framework, innovative behavior is interpreted as a nontrivial reorganization of an existing cognitive structure. New linguistic structures are generated by recombining nodes, substituting semantically compatible units, merging local substructures, or reconstructing relational paths while preserving acceptable semantic coherence. This interpretation does not equate innovation with arbitrary novelty; rather, it treats innovation as constrained structural variation within a meaningful semantic space. The resulting formulation provides the mathematical basis for the combinatorial generation model developed in the following sections.

B. Innovative Learning Objective Modeling

To formalize the cultivation of innovative ability in College English, the proposed framework models innovation-oriented learning as the dynamic evolution of a learner's cognitive structure within a discrete structural space. Conventional objectives often emphasize the acquisition and retention of knowledge, whereas innovation-oriented learning additionally requires learners to reorganize, transform, and generate structures from knowledge that is already available. Computational accounts of creativity likewise emphasize the importance of exploring and transforming structured conceptual spaces [17], while educational studies of problem-based and blended learning demonstrate the value of tasks that require active restructuring and problem solving [18]. From this perspective, innovative ability is represented not simply by an increase in the number of mastered knowledge units, but also by changes in how those units are connected, selected, and reorganized to produce semantically appropriate new expressions.

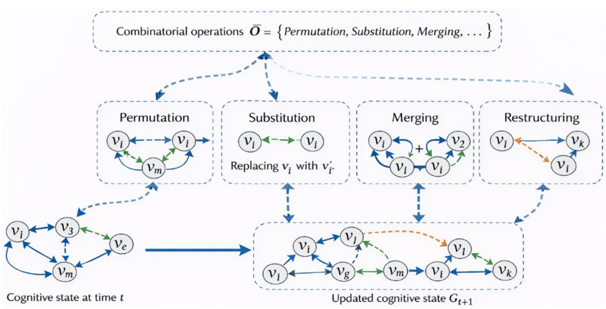

Figure 2: Schematic Diagram of the Innovative Learning Structure Mapping Framework Based on Combinatorial Operations

Figure 2 illustrates the combinatorial structure-mapping framework proposed for innovation-oriented learning. At time t, the learner's cognitive state is represented by the subgraph G_t, which contains the currently activated language-knowledge nodes and the structural relations established among them. Innovative learning is therefore modeled not as simple accumulation, but as a computational process in which the cognitive structure is systematically reorganized and allowed to evolve. As shown in Figure 2, the combinatorial operation set $\mathcal{O}$ specifies the transformations permitted during this process. Four basic operations are considered: permutation, substitution, merging, and reconstruction. Permutation changes the positional order of semantic units within an admissible syntactic structure. Substitution replaces an existing unit with a functionally or semantically related unit while preserving coherence. Merging integrates two or more local substructures into a higher-level expression, whereas reconstruction modifies dependencies among nodes to create a new expressive path. Through repeated application of these operations, the cognitive state evolves from G_t to G_{t+1}. The evolution may involve an increase in available units, but it may also involve changes in connectivity, dependency patterns, and structural organization. Innovation-oriented learning can therefore be represented as a constrained search over possible cognitive-graph transformations.

Based on the cognitive structure graph model constructed above, this paper formally defines the innovative learning process as a structure mapping function acting on the learner's cognitive subgraph, and its mathematical expression is as follows:

$$G_{t+1} = \mathcal{F}(G_t, \mathcal{O}), \tag{5}$$

where $G_t = (V_t, E_t)$ denotes the learner's cognitive state at time t, and G_{t+1} denotes the state obtained after an innovation-oriented learning operation or sequence of operations. The mapping function $\mathcal{F}(\cdot)$ characterizes the structural evolution mechanism. Its output can reflect both changes in the set of available knowledge units and changes in the connection patterns, dependencies, and organizational relations among those units.

The set $\mathcal{O}$ contains the combinatorial operations that may be applied to a cognitive structure and therefore constrains the admissible transformations during innovation generation. These operations abstract common forms of restructuring in language learning. Permutation adjusts the order of semantic units subject to syntactic constraints; substitution replaces a component with an equivalent, near-synonymous, or functionally compatible unit while maintaining semantic coherence; merging combines local substructures into a more complex linguistic structure; and reconstruction modifies dependency relations to create an alternative expression path. The operation set thus defines the discrete action space through which cognitive structures are transformed.

Within this modeling framework, innovation-oriented learning is viewed as a sequence of constrained combinatorial transformations of the cognitive graph. Repeated operations alter node availability, structural complexity, and connection patterns, thereby providing a computational representation of the transition from reproducing familiar expressions toward constructing new ones. The corresponding cognitive-evolution path is represented as follows:

$$G_0 \to G_1 \to \cdots \to G_t \to G_{t+1}. \tag{6}$$

Each state transition is generated by the structural mapping function $\mathcal{F}$ under the permitted operation set and semantic constraints.

The resulting objective model has two practical advantages. First, innovative behavior is represented within an explicit and computable structural operation space, which reduces reliance on purely qualitative descriptions of the concept of "innovation." Second, the formulation provides a direct basis for introducing combinatorial optimization algorithms. The innovation process can therefore be treated as a constrained structural-search problem in which candidate transformations are evaluated quantitatively. This connection between representation and optimization makes it possible to analyze innovative ability within a single computational framework while retaining an interpretable account of the structural changes produced by the model.

III. Deep Learning Semantic Modeling Methods

A. Transformer Semantic Encoder

To learn contextual semantic representations efficiently, this study adopts a hierarchical Transformer-based encoder–decoder architecture, whose overall organization is shown in Figure 3. The model contains an encoder for progressive semantic abstraction and a lightweight decoder for cross-level feature fusion. Its design combines multi-scale representation learning with cross-layer semantic integration so that local linguistic information and higher-level contextual information can be represented within a common embedding framework. The hierarchical encoder and multilayer-perceptron fusion design are informed by multiscale Transformer architectures [25], while the present application operates on linguistic representations rather than image pixels.

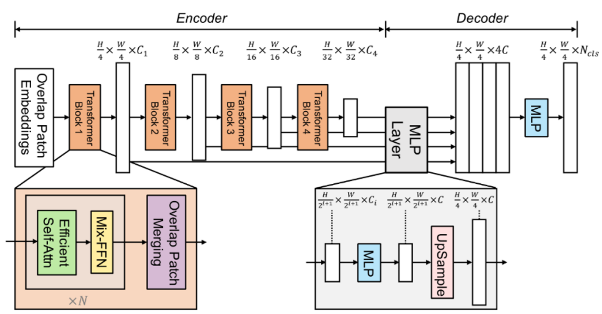

Figure 3: Architecture of the Hierarchical Transformer-Based Semantic Encoder–Decoder Network

At the input stage, the original text sequence is first mapped to continuous vectors. Initial local semantic features are then constructed through an overlapping embedding mechanism in which neighboring linguistic segments share contextual coverage. In the proposed implementation, this operation is referred to as Overlap Patch Embedding by analogy with hierarchical Transformer designs. The overlap is intended to preserve continuity across adjacent semantic units and to reduce the context fragmentation that can arise when a sequence is divided into nonoverlapping blocks. The resulting representation is then projected to a higher-dimensional feature space that serves as the input to subsequent contextual modeling.

During encoding, a four-level hierarchical Transformer progressively abstracts semantic features. As network depth increases, the representation is compressed while the feature dimension is expanded, allowing the model to move from relatively local lexical and phrasal patterns toward broader contextual and structural information. Related educational AI studies demonstrate the usefulness of multilevel neural representations for modeling learner-related information [19], [20], while the underlying attention mechanism follows the general Transformer principle [9]. Features produced at different stages therefore encode complementary semantic scales and together form a multilayer representation of the input.

The entire semantic encoding process can be uniformly represented as:

$$H = Transformer(X), \tag{7}$$

where X denotes the input semantic-embedding sequence and H denotes the contextual representation produced by the encoder.

Each Transformer block consists of a self-attention module and a feedforward network. By explicitly estimating dependencies between positions in the sequence, self-attention allows the model to capture long-range semantic associations that may be difficult to represent through strictly local operations. Its standard scaled dot-product form is given by:

$$Attention(Q, K, V) = softmax\left(\frac{QK^\top}{\sqrt{d_k}}\right)V. \tag{8}$$

This mechanism assigns context-dependent attention weights to linguistic positions, allowing the representation to emphasize information that is most relevant to the current semantic context.

In the feedforward stage, the model employs a Mix-FFN-style structure that combines linear transformation with local context-sensitive operations to enrich semantic features. A corresponding overlapping merging operation performs hierarchical compression between stages. Within the present language-modeling setting, these operations are used to reduce computational cost while retaining continuity among neighboring semantic units. Their role is architectural rather than linguistic: the linguistic meaning of the representation continues to be learned from the text and the attention-based context.

After hierarchical encoding, features from the different stages are supplied to the decoding module. A multilayer perceptron (MLP) aligns the feature dimensions of the stage outputs, and the aligned representations are mapped to a common sequence-level resolution before fusion. This procedure combines local and global semantic information across layers and produces a unified representation suitable for the subsequent cognitive-graph and combinatorial modules.

Let F_i denote the encoded feature produced by stage i. The fusion process is represented as:

$$F = Fuse(F_1, F_2, F_3, F_4). \tag{9}$$

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Finally, the fused features are transformed into a unified semantic representation by the output mapping layer:

$$Y = MLP(F). \tag{10}$$

The resulting representation combines global contextual information with local structural cues and provides the continuous semantic embeddings used to initialize cognitive-graph nodes. These embeddings also supply distance and coherence information for the combinatorial structural-reorganization stage described below.

B. Latent Semantic Embedding Space

Following contextual encoding, discrete linguistic units are mapped into a continuous latent semantic space so that symbolic knowledge structures and combinatorial operations can be linked to measurable semantic relations. The objective is to construct a representation space in which linguistic units can be compared, constrained, and optimized in vector form, complementing the discrete graph representation used elsewhere in the framework [21]. Figure 4 summarizes this construction process. Words, phrases, and grammatical structures are first represented symbolically as knowledge nodes and are then projected, through a nonlinear semantic mapping, into continuous vectors that encode their contextual properties.

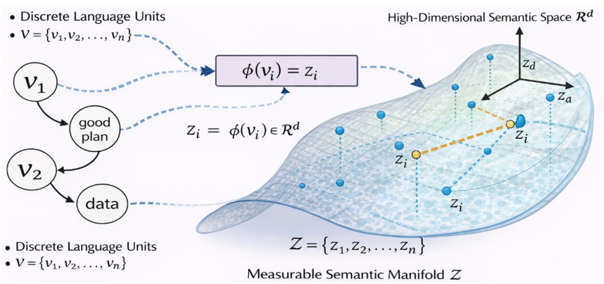

Figure 4: Construction of the Latent Semantic Embedding Space

For a linguistic knowledge unit $v_i \in V$ in the cognitive graph, the corresponding latent semantic embedding is defined as:

$$z_i = \phi(v_i) \in \mathbb{R}^d, \tag{11}$$

where $\phi(\cdot)$ denotes the nonlinear mapping implemented by the Transformer encoder and the associated projection network, and d is the dimension of the latent semantic space. Through this mapping, discrete lexical items, chunks, and grammatical structures are represented in a common vector space. The mapping does not remove their symbolic identities in the cognitive graph; rather, it supplies each node with a continuous representation that can be used for semantic comparison and optimization.

The embedding vectors of all language knowledge units together constitute a high-dimensional semantic representation set:

$$\mathcal{Z} = \{z_1, z_2, \ldots, z_n\}. \tag{12}$$

The set $\mathcal{Z}$ can be interpreted as a learned semantic geometry embedded in a Euclidean vector space. Under the modeling assumption used here, units that are semantically similar tend to occupy nearby regions of the representation space, whereas units with larger semantic differences tend to be farther apart. This geometric view makes it possible to express semantic proximity numerically and to use that information when constraining structural transformations.

In the latent semantic space, semantic separation between two units may be quantified using an appropriate metric. In the experiments reported here, the Euclidean form can be written as:

$$d(z_i, z_j) = \|z_i - z_j\|_2 . \tag{13}$$

This distance measure provides an explicit constraint for the subsequent combinatorial search. On the one hand, limiting semantic displacement can prevent candidate transformations from moving too far from the intended meaning. On the other hand, controlled displacement can contribute to the novelty term of the innovation objective by measuring how far a new structure moves from its source representation. Semantic distance therefore serves two complementary purposes: preserving coherence and quantifying controlled novelty.

The latent semantic space complements rather than replaces the symbolic graph representation. As a result, innovation-oriented learning can be modeled simultaneously in a discrete structural space and a continuous semantic space. The graph specifies which linguistic units and relations are being reorganized, while the embedding space quantifies semantic similarity, displacement, and coherence. This dual representation provides the foundation for the structural recombination and quantitative evaluation procedures developed in the next section.

IV. Combinatorial Mathematics-Driven Innovative Generative Models

After semantic representations and the latent embedding space have been constructed, innovation generation is modeled from a combinatorial perspective. Innovative behavior is treated as a constrained reorganization of available semantic units and therefore as a search-and-optimization problem over a discrete structural space. This formulation is consistent with recent efforts to combine deep learning with intelligent English teaching and innovation-oriented educational modeling [22], [23]. Figure 5 summarizes the proposed combinatorial generation process. Given a set of available semantic units, the admissible selections and structural transformations define a combinatorial hypothesis space whose size grows rapidly with the number of units and permissible operations. An initial collection of candidate structures is generated through sampling, after which each candidate is evaluated using an innovation objective that combines semantic novelty, semantic coherence, and structural complexity. Because exhaustive enumeration becomes infeasible as the search space expands, approximate optimization is used. A genetic algorithm explores the space through selection, crossover, and mutation; beam search retains multiple high-quality partial candidates during sequential generation; and reinforcement learning guides the selection of structural operations through policy updates. Together, these mechanisms provide complementary strategies for exploring high-value regions of the combinatorial search space without requiring exhaustive enumeration.

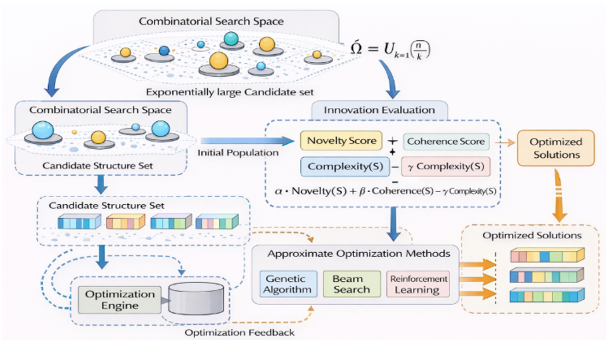

Figure 5: Schematic Diagram of Combinatorial Search Space and Innovation Generation Optimization Process

A. Combinatorial Hypothesis Space

Let n denote the number of semantic units available for innovation generation in the current learning context. These units may have different granularities, including lexical items, phrases, and higher-level grammatical structures. Before ordering and relational constraints are imposed, the basic selection space can be represented as the family of all nonempty subsets of the available unit set V_t. Accordingly, the selection component of the theoretical hypothesis space is defined as:

$$\Omega = \bigcup_{k=1}^{n} \{S \subseteq V_t : |S| = k\}. \tag{14}$$

The subset family has cardinality $|\Omega| = 2^n - 1$ before structural ordering, dependency, and operation-specific constraints are considered. Thus, even the selection component of innovation generation grows exponentially with n. Permutation, substitution, merging, and reconstruction further differentiate candidate structures that may contain the same underlying units but organize them in different ways.

The complete hypothesis space therefore contains both alternative selections of semantic units and alternative structural organizations of those selections. Its effective size grows at least exponentially as the number of available units increases and grows further when admissible structural transformations are taken into account. Exhaustive search is consequently impractical for realistic inputs. The innovation-generation task is therefore treated as a high-dimensional discrete optimization problem, which motivates the use of approximate search algorithms in the subsequent solution stage.

B. Innovation Generation Optimization Function

To select innovative language structures from a vast combinatorial hypothesis space, this paper constructs a multi-objective joint optimization function to comprehensively evaluate the innovation quality of candidate structures. The innovation generation objective function is defined as:

$$\max_{S\in\Omega} \left[\alpha\, Novelty(S) + \beta\, Coherence(S) - \gamma\, Complexity(S)\right], \tag{15}$$

where S denotes a candidate structure in the combinatorial space Ω, and α, β, and γ are nonnegative weighting coefficients that control the relative importance of the three objectives. Complexity enters with a negative sign because it is treated as a penalty rather than as a quantity to be maximized.

The term $Novelty(S)$ measures the semantic displacement of a candidate structure relative to the source cognitive structure; larger values represent greater novelty in the latent semantic space. $Coherence(S)$ evaluates semantic coherence and contextual compatibility so that structurally novel candidates remain linguistically interpretable. $Complexity(S)$ quantifies structural burden and therefore penalizes unnecessarily elaborate or redundant candidates. The three terms are normalized before weighted combination so that no objective dominates solely because of scale differences.

This objective transforms innovation generation into a multi-criteria optimization problem in which novelty, linguistic rationality, and structural economy must be balanced. Rather than equating innovation with maximal semantic deviation, the formulation rewards controlled novelty that remains coherent while avoiding unnecessary structural expansion. It therefore provides a transparent mathematical interpretation of the trade-offs that govern candidate selection.

C. Solution Method

Because the effective hypothesis space grows exponentially and combines discrete selection with structural transformations, exact enumeration is computationally prohibitive for realistic problem sizes. The resulting search problem is therefore approached with established approximate optimization strategies rather than with exhaustive enumeration. Genetic algorithms are particularly suitable for large combinatorial search spaces because they use population-based selection and variation to explore candidate solutions [24].

First, a genetic algorithm (GA) is used to model recombination and variation during innovation generation. Candidate structures are encoded as individuals, and selection, crossover, and mutation are repeatedly applied so that the population can explore diverse structural regions while retaining higher-scoring solutions.

Second, beam search retains a fixed number of the highest-scoring partial candidate paths at each generation step. The finite beam width reduces the number of structures that must be expanded and thereby provides a tractable approximation to a broader search while preserving several alternative candidate trajectories.

Third, reinforcement learning (RL) represents innovation generation as a sequential decision process. A policy network selects among admissible combinatorial operations, receives feedback from the innovation objective, and progressively favors operation sequences associated with higher-valued structures.

The three approximate methods are used as complementary search mechanisms rather than as evidence of exact optimality. Together, they allow the model to explore candidate language structures in a large combinatorial space at manageable computational cost. Their outputs can then be evaluated under the same novelty, coherence, and complexity criteria, enabling systematic comparison of optimization behavior and downstream innovation scores.

V. Experimental Design and Results Analysis

This section evaluates the proposed deep-learning and combinatorial innovation-generation model through a series of controlled experiments on language-oriented tasks. The evaluation focuses on semantic representation quality, innovation-generation performance, structural controllability, and computational efficiency. The proposed framework is compared with several representative baseline methods so that the contribution of semantic modeling, heuristic search, and combinatorial optimization can be examined under a common evaluation protocol.

A. Experimental Environment and Dataset

All experiments were conducted in a unified hardware and software environment. The platform used Ubuntu 20.04, an Intel Xeon 6248 processor, and an NVIDIA RTX 3090 GPU with 24 GB of video memory. The deep-learning components were implemented in PyTorch 2.0 with Python 3.10. Mixed-precision computation was used during training and inference to reduce memory consumption and improve computational efficiency. Keeping the software stack and hardware configuration fixed across the reported comparisons also reduced variation attributable to the execution environment.

The experimental data were drawn from an authentic university-level English writing corpus containing several types of creative language tasks, including argumentative essay writing, summary reconstruction, and opinion rewriting. The corpus contains 18,742 English text samples, has an average sentence length of 21.6 words, and comprises approximately 2.4 million tokens in total. Automatic semantic parsing and syntactic dependency analysis were applied to the source texts to construct the language-knowledge graph used by the model. This preprocessing produced 12,368 semantic units spanning several linguistic levels, including lexical units, fixed phrases, and syntactic templates. In addition, 3,200 texts were randomly selected and manually assigned innovation scores. These annotated samples were used to align the evaluation criterion during model development and to assess the correspondence between computational innovation scores and human-assigned labels.

B. Experimental Setup and Evaluation Methods

The Transformer semantic encoder uses a four-stage hierarchical configuration for representation learning. The embedding dimension is 768, self-attention uses 12 heads, the feedforward hidden dimension is 3072, and dropout is set to 0.1 during training to reduce overfitting. In the combinatorial stage, the GA population size is 100 and the maximum number of generations is 50. Beam search uses a width of 10 so that several high-scoring candidate paths remain available at each expansion step. The reinforcement-learning module uses a discount factor of 0.99 to place substantial weight on longer-term rewards while retaining sensitivity to immediate feedback. These settings are held fixed in the principal model comparisons unless a parameter is varied explicitly in the sensitivity analysis.

Several representative generation approaches are selected as baselines. The rule-based method constructs outputs from manually specified templates and linguistic rules and therefore represents a conventional symbolic approach. The Seq2Seq model with long short-term memory (LSTM) provides a recurrent neural baseline for sequence generation. A Transformer-only model is included to isolate the contribution of contextual semantic modeling without explicit combinatorial search. A Transformer combined with beam search is used to evaluate the effect of heuristic candidate retention during generation. Finally, the complete proposed model integrates deep semantic representation with explicit combinatorial structure search. Comparing these systems under the same evaluation criteria makes it possible to distinguish improvements associated with semantic representation from those associated with the structural optimization mechanism.

The evaluation framework contains three primary dimensions: semantic novelty, semantic coherence, and structural complexity. Semantic novelty measures the controlled semantic displacement of a generated candidate relative to the source cognitive structure and therefore captures one aspect of innovation. Semantic coherence measures contextual compatibility and semantic rationality within the generated structure. Structural complexity measures the amount of structural expansion or redundancy and is interpreted as a cost, so lower values are preferred when semantic quality is comparable. The three normalized indicators are combined into the comprehensive innovation score introduced earlier. This multidimensional design is intended to prevent a model from obtaining a high innovation assessment merely by producing extreme semantic deviations or unnecessarily complicated structures.

C. Experimental Results and Analysis

1) Comparison of Overall Performance

Table 1 presents a comparison of the comprehensive performance of different methods on the innovation generation task. Overall, the proposed method achieves the strongest overall values across the reported core metrics, providing empirical support for its effectiveness in the present innovation-modeling task. Analysis of semantic novelty metrics shows that rule-based methods, relying on template structures, exhibit the lowest novelty. Seq2Seq and Transformer models show a gradual improvement trend with enhanced semantic modeling capabilities, but remain constrained by implicit sequence generation mechanisms. Our proposed method, by

Table 1: Comprehensive Experimental Results on Innovation-Oriented Generation

Method	Novelty ↑	Coherence ↑	Complexity ↓	Innovation ↑	Δ Innovation (%)	Runtime (ms) ↓
Rule-based	0.31 ± 0.02	0.72 ± 0.03	1.89 ± 0.06	0.42 ± 0.03	—	95
Seq2Seq (LSTM)	0.44 ± 0.03	0.76 ± 0.03	1.72 ± 0.05	0.55 ± 0.04	+31.0%	210
Transformer	0.58 ± 0.02	0.81 ± 0.02	1.63 ± 0.04	0.67 ± 0.03	+21.8%	320
Transformer + Beam	0.62 ± 0.02	0.83 ± 0.02	1.61 ± 0.04	0.71 ± 0.03	+6.0%	410
Proposed Method	0.79 ± 0.01	0.86 ± 0.01	1.42 ± 0.03	0.84 ± 0.02	+18.3%	360

introducing combinatorial mathematical structure recombination, achieves a novelty score of 0.79, approximately 27% higher than the best baseline model, indicating a marked expansion of the explored innovation space. Regarding semantic coherence, the differences among methods are comparatively modest, but the proposed model maintains the highest reported coherence level while achieving high novelty, indicating that the latent semantic embedding space and distance constraint mechanism effectively avoid semantic distortion. Structural complexity results show that traditional methods generally suffer from structural redundancy, while our model achieves a more compact structural expression through complexity penalties. In terms of comprehensive innovation score, our proposed method reaches 0.84, approximately 18% higher than Transformer+Beam, providing the strongest observed balance among novelty, coherence, and structural controllability in the reported comparison.

To systematically analyze the specific roles of each model component in the innovation generation process, this paper designs multiple ablation experiments. By gradually removing key modules, the impact on the overall model performance is evaluated. The ablation experiments mainly focus on three core components: combinatorial mathematical modeling mechanism, semantic distance constraint, and structural complexity penalty.

Ablation model settings:

w/o Combinatorial Optimization: Removes the combinatorial mathematical structure search, using only Transformer semantic generation;

w/o Semantic Distance Constraint: Retains the combinatorial search structure but does not constrain the semantic offset magnitude;

w/o Complexity Penalty: Removes the structural complexity penalty term;

Full Model: The complete model.

As can be observed from Table 2, the contributions of the individual modules to model performance are materially different. First, when the combinatorial mathematical optimization mechanism is removed, the model's overall innovation score drops from 0.84 to 0.69, a decrease of approximately 18%, indicating that relying solely on deep semantic modeling is insufficient to effectively characterize the structural innovation process, and combinatorial structure search plays a decisive role in innovation generation. After removing the semantic distance constraint, the model shows some improvement in semantic novelty, but semantic coherence decreases, while structural complexity increases, ultimately leading to a decrease in the overall innovation score to 0.72. This shows that in the absence of semantic embedding space constraints, although the model can generate larger semantic shifts, it is often accompanied by semantic distortion and expression instability. When the complexity penalty term is removed, the model's novelty remains at a high level, but the generated structural complexity increases markedly, manifested in an increase in redundant nodes and invalid structures, ultimately resulting in an innovation score of only 0.75. This result verifies the important role of structural complexity constraints in balancing innovativeness and usability.

Figure 6 illustrates the performance trends of the innovation-generation model under different parameter configurations, analyzing the impact of novelty weight α, consistency weight β, and structural complexity penalty coefficient γ on the model output. It can be observed that as α increases, the semantic novelty index increases substantially. However, when α exceeds 0.4, semantic coherence decreases and structural complexity rises rapidly, leading to a decline in the overall innovation score. This indicates that overemphasizing novelty can easily trigger semantic drift. Changes in β mainly affect the semantic stability of the generated results. Moderately increasing β helps enhance semantic coherence, but when its value is too large, novelty is suppressed, causing a noticeable contraction of the innovation space. The γ parameter directly controls the structural compactness. When γ is small, the generated structure contains substantial redundancy, while excessive penalty limits the expansion of effective structures, thus reducing the overall innovation capability. Considering the trends of various indicators, when α=0.4, β=0.4, and γ=0.2, the model achieves the optimal balance between semantic novelty, semantic coherence, and structural complexity, corresponding to the highest overall innovation score.

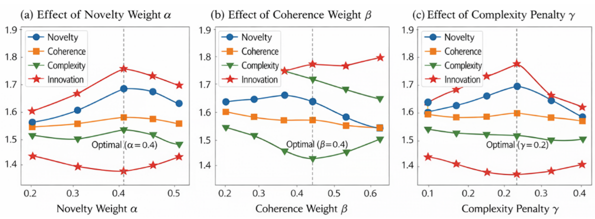

Figure 6: Sensitivity Analysis of Parameter Weights (α, β, γ)

Figure 7 shows the overall distribution of innovation scores for traditional rule-based methods, the Transformer-only model, and the innovation-generation model proposed in this paper. The bar chart reflects the sample frequency distribution, and the kernel density curve depicts the overall

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Table 2: Ablation Study Results on Innovation-Oriented Generation

Model Variant	Novelty ↑	Coherence ↑	Complexity ↓	Innovation ↑	Runtime (ms)
w/o combinatorial optimization	0.61 ± 0.02	0.84 ± 0.01	1.59 ± 0.04	0.69 ± 0.03	280
w/o semantic distance constraint	0.74 ± 0.02	0.78 ± 0.03	1.71 ± 0.05	0.72 ± 0.03	330
w/o complexity penalty	0.77 ± 0.01	0.82 ± 0.02	1.93 ± 0.06	0.75 ± 0.04	345
Full model	0.79 ± 0.01	0.86 ± 0.01	1.42 ± 0.03	0.84 ± 0.02	360

probability trend. It can be observed that the innovation scores of traditional rule-based methods are mainly concentrated in the 0.25–0.45 range, with a pronounced concentration toward the lower-score range, indicating that their generation results are highly dependent on the template structure and struggle to produce innovative expressions with significant semantic shifts. The Transformer model's score distribution shifts to the right overall, with peaks concentrated in the 0.45–0.65 range, indicating that deep semantic modeling can expand the semantic combination space to some extent, but its proportion of high-scoring samples remains limited. In contrast, the proposed method exhibits a clear rightward shift in the innovation-score distribution, with its main peak located in the 0.65–0.80 range, and a clear density advantage in the high-score segment ($\geq$0.7), indicating that the improvement in innovation capability is not driven by a small number of extreme samples, but rather by a systematic improvement in the overall generation results.

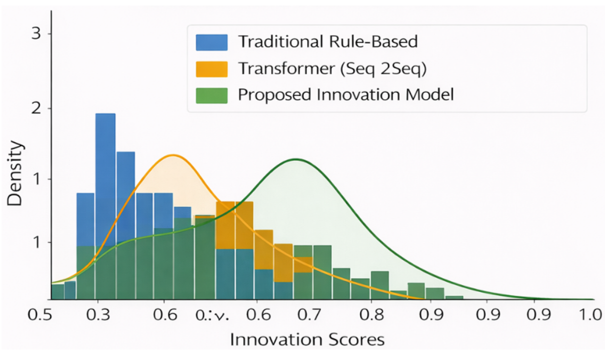

Figure 7: Comparison of Innovation Score Distribution Under Different Methods (Histogram–KDE)

Figure 8, presented as a violin diagram, compares the distribution characteristics of traditional rule-based methods, the Transformer-only model, and the proposed innovation-generation model across multiple evaluation metrics, including semantic novelty, consistency, structural complexity, and overall innovation score. It can be observed that while traditional rule-based methods exhibit a relatively stable distribution pattern in terms of consistency, their novelty and innovation scores are generally low, reflecting the inherent limitations of template-driven methods in innovative expression. The Transformer model improves upon rule-based methods in both novelty and consistency, but its distribution range is relatively concentrated, with a limited proportion of high-scoring samples, indicating that it primarily relies on implicit semantic transformations and struggles to achieve deep structural innovation. In contrast, the proposed method shows a significant rightward shift in both novelty and overall innovation score, with the median and upper quartile higher than those of the comparison methods. Furthermore, its distribution pattern is more concentrated, demonstrating better stability and robustness while enhancing innovation capabilities. It is worth noting that, in terms of structural complexity, the distribution of the proposed method is shifted toward lower complexity values than those of the other models, indicating that the optimization strategy driven by combinatorial mathematics effectively suppresses the expansion of redundant structures, making the innovative expression more compact and controllable while maintaining semantic diversity.

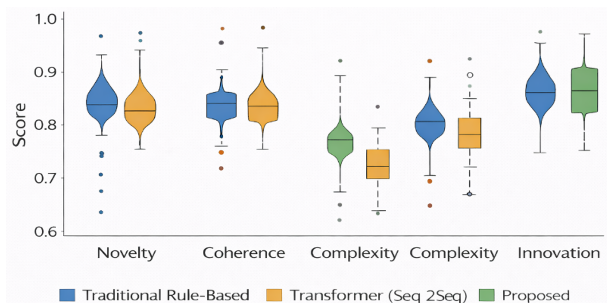

Figure 8: Distribution of Different Methods on Multidimensional Evaluation Indicators

Figure 9 illustrates the performance distribution characteristics of different methods in the innovation generation task from a multi-objective optimization perspective. It presents the scatter plot distribution under two key dimensions: "semantic novelty – semantic coherence" and "comprehensive innovation score – structural complexity," with the theoretical Pareto front marked by dashed lines. It can be observed that traditional rule-based methods mainly generate samples distributed in regions of low novelty or low consistency, making it difficult to simultaneously consider semantic rationality and innovation. The Transformer-only model improves on the novelty dimension, but its scatter plots are still concentrated within the Pareto front, indicating that its innovation capability mainly comes from continuous semantic transformations and lacks a structural optimization mechanism. In contrast, the innovation-generation model proposed in this paper clusters more strongly toward the upper-right region of the Pareto front in both subfigures, maintaining good semantic coherence under high novelty conditions and achieving a higher comprehensive innovation score under controlled structural complexity. This phenomenon demonstrates that combinatorial mathematical modeling based on the latent semantic embedding space effectively expands the feasible solution space, enabling the model to continuously approach the optimal trade-off region under multi-objective constraints.

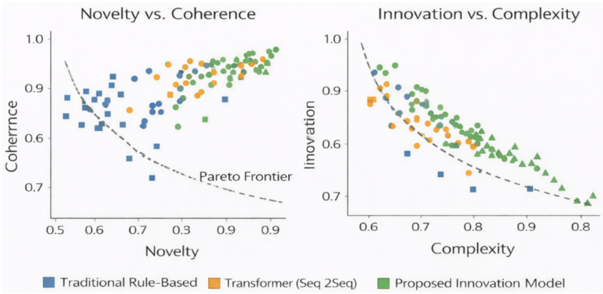

Figure 9: Pareto Frontier Analysis of Innovation Generation Results

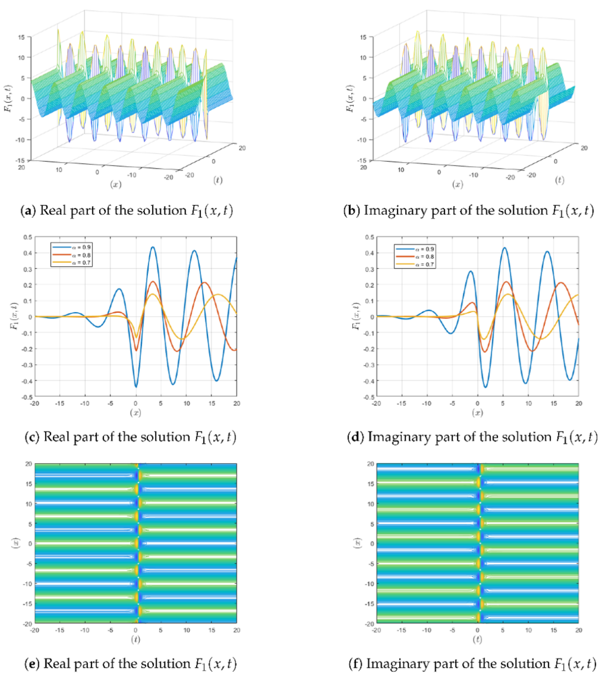

Figure 10: Spatiotemporal Evolution Visualization of the Dynamic Process of Innovation Generation

Figure 10 presents the dynamic evolution characteristics of latent semantic states during innovation generation in a multi-scale spatiotemporal visualization. Subfigures (a)–(b) show the three-dimensional variation trends of the real and imaginary parts of the semantic state function in continuous time and semantic space, respectively, reflecting the overall fluctuation structure of innovation generation in the high-dimensional embedding space. Subfigures (c)–(d) show the semantic response curves corresponding to different parameter configurations at a fixed time section, indicating that the generation structure varies across the different innovation-weight settings. Subfigures (e)–(f) depict the overall propagation pattern of semantic states over time in the form of heatmaps. It can be observed that under the influence of the latent semantic embedding space and the combinatorial mathematics-driven optimization mechanism proposed in this paper, the semantic state evolution process exhibits a stable and orderly periodic structure, without the random oscillations or divergence caused by unconstrained search. This continuous and controllable dynamic characteristic indicates that innovation generation is not a random recombination, but an orderly structural migration process guided by multi-objective constraint functions.

Figure 11 illustrates the evolution trend of learning accuracy for different learner groups under varying average response times from a learning behavior perspective, reflecting the dynamic characteristics of the English learning process supported by the model. The horizontal axis represents the learner's average logarithmic response time in the task, and the vertical axis represents the corresponding learning accuracy. The curves and their confidence intervals depict the overall trend of learning performance as cognitive input changes. It can be observed that, regardless of the overall sample or different groups such as gender, whether or not they have an Individualized Education Program (IEP), and whether they are English learners (ELs) or non-English learners (Non-ELs), learning accuracy exhibits a significant "S-shaped" upward trend with increasing response time, indicating that within a reasonable time investment range, learning effectiveness can be steadily improved. Notably, the performance curves of each subgroup tend to plateau after reaching the medium-to-high accuracy range, indicating that the proposed learning support model based on semantic embedding and combinatorial optimization can form a consistent learning gain pattern under different learning foundations, rather than being effective only for specific groups. Furthermore, the response times of different groups at key accuracy thresholds (such as 0.7 and 0.8) are relatively similar, indicating broadly similar response-time requirements across the plotted groups at those accuracy levels.

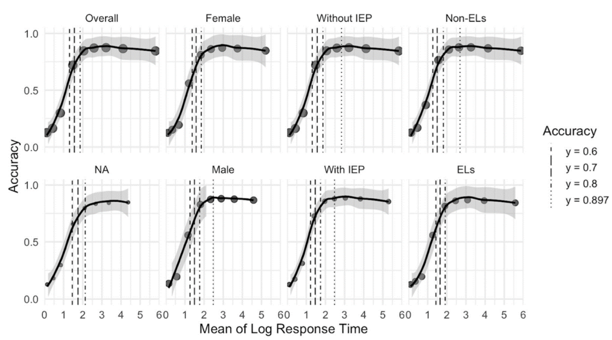

Figure 11: Relationship Between Learning Performance and Response Time Among Different Learner Groups

Figure 12 systematically illustrates the performance changes of different learner groups in English learning tasks from the perspective of learning decision threshold adjustment. The blue dashed line represents the trend of learning accuracy with the threshold parameter, and the red dashed line represents the change in average response time. It can be observed that across all participants and different subgroups (gender differences, whether or not they have individualized education plans, and English learners versus non-English learners), learning accuracy shows a stable upward trend with increasing threshold parameter, while response time increases synchronously, reflecting a typical "accuracy-efficiency" trade-off. Compared with the baseline threshold setting, the selected threshold after dynamic adjustment by the proposed model shifts to the left in all groups, while the plotted curves indicate that comparable accuracy can be maintained with a lower average response time, indicating that the proposed innovative learning path can effectively improve learning efficiency. Notably, different learner groups show a broadly consistent adjustment trend near the selected operating threshold, indicating that the plotted threshold-response pattern is broadly comparable across the reported learner groups.

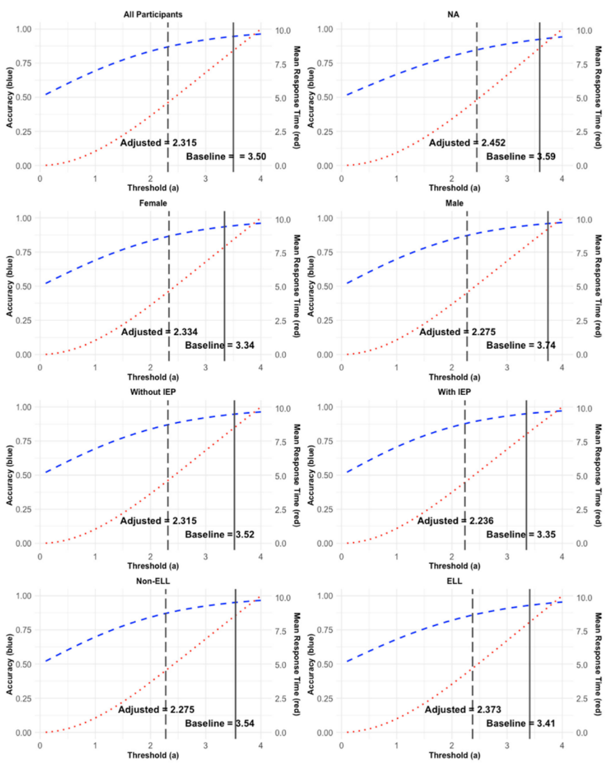

Figure 12: The Impact of Learning Threshold Adjustment on Accuracy and Response Time for Different Learner Groups

Figure 13 systematically illustrates the dynamic trends of the model's learning accuracy across various English grammatical structure tasks during the training process, covering typical linguistic phenomena such as subject-verb agreement, interrogative structures, determiner agreement, filler–gap dependencies, island constraints, quantifier structures, negative-polarity licensing, argument structures, and referential agreement. The horizontal axis represents the number of training steps, the vertical axis represents the prediction accuracy for the corresponding task, and the shaded area represents the confidence interval. It can be observed that in most basic grammatical structure tasks, all training strategies can quickly achieve high accuracy levels. However, in tasks involving long-distance dependencies and complex syntactic constraints (such as relative clause agreement, wh-dependencies, island effects, and binding principles), clear performance differences emerge among the compared training strategies. Compared to single-stage training methods, two-stage training and hybrid training strategies converge faster and are more stable on complex structure tasks, demonstrating stronger structural generalization ability. This phenomenon is highly consistent with the latent semantic embedding space and combinatorial structure modeling ideas proposed in this paper, indicating that explicitly modeling language structural relationships and introducing a phased learning mechanism helps the model gradually form a stable syntactic cognitive structure.

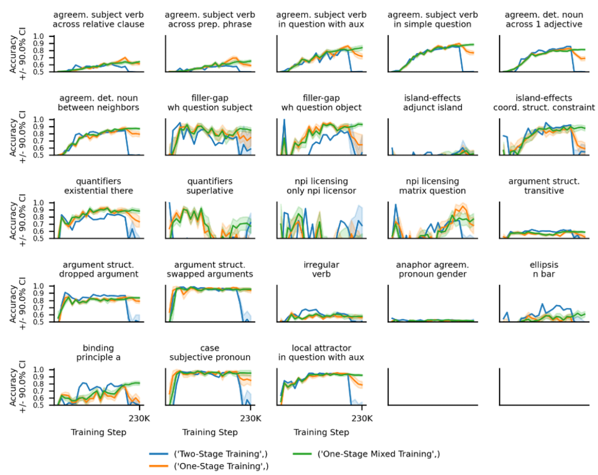

Figure 13: Comparison of Learning Performance Evolution on Different Grammatical Structure Tasks

Figure 14, with the learning task progression process as the horizontal axis, illustrates the trajectory of ability changes among students of different English learning levels during continuous learning activities. The light-colored curves represent individual learning paths, while the dark-colored curves represent the average trend of the corresponding level groups. It can be observed that lower-level learners exhibit pronounced ability gains in the initial stage, with a steeper reported improvement trajectory than that of the intermediate- and high-level groups, indicating that the innovative learning path proposed in this paper has a stronger promoting effect on learners with weak foundations. As the number of learning tasks increases, the performance of all level groups shows a stable upward trend and gradually converges, reflecting the consistent guiding effect of latent semantic embedding and combinatorial optimization mechanisms across different ability levels. The changes in newly added nodes and reconstructed edges in the figure further illustrate that the improvement of learning ability does not simply rely on repetitive training, but is achieved through the continuous expansion and reorganization of cognitive structures.

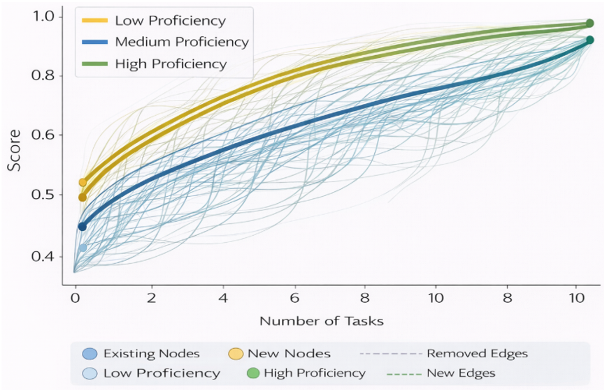

Figure 14: Trajectory of Ability Improvement During the Learning Task Progression at Different English Learning Levels

VI. Conclusion

This paper addresses the computational modeling and evaluation of innovative ability in College English learning by proposing a framework that integrates deep learning with combinatorial mathematics. A Transformer-based semantic encoder maps discrete linguistic knowledge into a continuous latent embedding space, while a cognitive graph provides an explicit structural representation of the learner's available knowledge units and their relations. Innovation generation is subsequently formulated as a multi-objective combinatorial optimization problem that balances semantic novelty, semantic coherence, and structural complexity. Genetic algorithms, beam search, and reinforcement learning are used as approximate search strategies for exploring the resulting structural space. The experiments on the reported College English writing corpus show that the proposed method attains higher innovation scores than the comparison methods, shifts the innovation-score distribution toward higher values, and maintains comparatively compact generated structures. The ablation and sensitivity analyses further indicate that combinatorial search, semantic-distance constraints, and complexity regularization contribute differently to the observed performance. Multidimensional visualizations provide additional descriptive evidence concerning cognitive-structure evolution, optimization behavior, and differences among learner groups. Taken together, the results support the value of combining continuous semantic representation with explicit structural optimization when modeling innovation-oriented language learning. Future work should extend the framework to multimodal learning data, evaluate it with longer longitudinal observations, and test its robustness across additional institutions, learner populations, and authentic instructional settings. Such extensions would provide a stronger basis for assessing generalizability and for translating the computational framework into practical educational support tools.

Data Availability

The data required to support the findings of this study are included within the manuscript.

Conflicts of Interest

The author declares that there are no conflicts of interest related to this work.

Funding

This research received no external funding.

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