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Article

POA-MLSP: a multi-dimensional learning analytics framework for predicting CET4 writing performance based on a production-oriented approach and student engagement patterns

Yu Li[1], Nur Ainil BT. Sulaiman[1*], Halizah BT. Omar[2]

[1]Faculty of Education, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor, Malaysia
[2]Pusat Pengajian Citra Universiti, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor, Malaysia

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*Corresponding author
Email address:
nurainil@ukm.edu.my

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A B S T R A C T

Contemporary College English Test Band 4 (CET-4) writing instruction faces significant challenges in accurately predicting student performance and providing timely pedagogical interventions. This study develops and validates the Production-Oriented Approach Multi-Dimensional Learning Analytics Framework for Student Performance (POA-MLSP) for predicting CET-4 writing performance across five dimensions through systematic integration of Production-Oriented Approach (POA) theory and Self-Determination Theory (SDT)-based engagement modeling. The framework implements a four-layer architecture incorporating Feature Adaptive Selection Mechanism and SDT-Based Engagement Dynamic Modeling algorithms. Validation involves 124 students during a 16-week semester, collecting multi-source data including Jacobs' five-dimensional assessments, Utrecht Work Engagement Scale-Student (UWES-S) engagement measurements, classroom observations, and digital platform interactions across experimental and control groups. POA-MLSP achieves R^2 = 0.75 overall prediction accuracy, outperforming linear regression (R^2 = 0.58), random forest (R^2 = 0.66), and support vector machines (R^2 = 0.63) by 17-29%. Content prediction reaches highest accuracy (R^2 = 0.78), while the framework identifies five distinct engagement profiles and achieves 78.4% ± 2.1% early warning accuracy with 79.8% ± 2.9% teacher satisfaction. Educational theory-guided algorithms significantly enhance prediction performance while maintaining pedagogical interpretability, enabling proactive intervention through early warning systems with minimal implementation burden for authentic educational applications.

1. Introduction

The Production-Oriented Approach (POA) has emerged as a revolutionary pedagogical framework within Teaching English as a Foreign Language (EFL) contexts, representing a paradigmatic shift from input-based teaching methodologies toward a more integrative theory-driven pedagogical process designed to enhance comprehensive learning outcomes. Contemporary research demonstrates that POA implementation within tertiary educational contexts effectively bridges the gap between language learning and language utilization through its comprehensive three-stage instructional model encompassing motivating, enabling, and assessing phases [1]. The theoretical depth of POA comes through multi-theoretical fusion (systematic integration of complementary educational frameworks) unifying several of the most basic theoretical frameworks, such as Krashen's Input Hypothesis, Vygotsky´s Social Constructivism and cognitive processing theories of writing development, as well as sociocultural perspectives of language learning, in a multi-faceted approach that attends to various dimensions of language learning paths at the same time [2]. Classroom practices and implementations suggest that POA-based instruction is highly effective at improving student writing performance on a range of competencies when partnered with reciprocal teaching models that leverage peer interaction and collaborative learning channels [3]. The capability of POA to encompass both general and business. English teaching, as well as specialized academic teaching, is a testimony to its theoretical robustness and practical fit for diverse learning goals and student groups [4].

Abbreviations

AI	Artificial Intelligence
CEFR	Common European Framework of Reference
CET-4	College English Test Band 4
DLAs	Digital Learning Activities
EDA	Educational Data Analytics
EFL	English as a Foreign Language
MAE	Mean Absolute Error
ML	Machine Learning
MLSP	Multi-dimensional Learning Analytics Framework for Student Performance
POA	Production-Oriented Approach
R^2	Coefficient of Determination
RMSE	Root Mean Square Error
SDT	Self-Determination Theory
SVM	Support Vector Machine
TVA	Traditional Approach
UWES-S	Utrecht Work Engagement Scale-Student

Contrary to the studies described in the previous sections which investigated the effects of POA on language learning in comparison to that of TVA, recent POA experiments carried out in the context of university Classrooms in China show the success of POA in ameliorating learner motivation and engagement, factors that, up to now, have been depression paving the way for language learning progress [5]. The inclusion of components such as cultural features and technology-enhanced learning environments in POA frameworks reflects the comprehensiveness of the approach to change and its ability to evolve and respond to the needs of modern education [6, 7]. More advanced applications of POA in the flipped classroom, as well as teacher training programs, reveal the scalability and potential of the approach to revolutionize language education at various educational levels and professional development contexts [8, 9]. Theoretical underpinnings of student engagement in POA instruction. Based on Self-Determination Theory (SDT), which yields important understandings about the motivational factors that are associated with language learning effectiveness and the intricate relationship between psychological need fulfilment and academic achievement, student engagement in POA instruction has been extensively argued. Studies show that learning environments in which freedom of choice, competence, and socially relatedness are supported can be conducive to sustained involvement and enhanced learning outcomes [10].

The difference between intrinsic and extrinsic motivation orientations is especially important in the context of a POA, as challenging activities on unlimited progression levels or limited progression levels must strike a balance between challenge and the capability level of the learner to ensure that motivation remains at a high level and no disengagement occurs [11]. DLAs provide opportunities for the facilitation of students' engagement through well-designed technological interventions, which are in alignment with SDT, especially in blended learning settings where the conventional classroom environment is complemented with online elements [12]. During this transition to the pandemic mode of online learning, a better understanding of what drives students to engage across different delivery and online modalities has also become clear, demonstrating the power of ensuring sustained psychological need satisfaction regardless of delivery form [13]. Collaborative learning approaches within English language programs demonstrate significant potential for enhancing engagement through peer support mechanisms, though the effectiveness of such interventions depends heavily on group dynamics and task design considerations [14]. The complex relationships between motivational factors, including the mediating effects of emotional states and the fulfillment of basic psychological needs, create dynamic engagement patterns that directly influence learning behaviors and academic outcomes [15]. Contemporary research into self-directed e-learning environments reveals the critical role of social support, self-regulated learning strategies, and flow experiences in sustaining long-term engagement with language learning activities [16].

The application of educational data mining and learning analytics to language instruction represents an emerging frontier that offers substantial potential for understanding and predicting student performance patterns, though the integration of these technologies with established pedagogical theories remains largely unexplored. Systematic reviews of predictive modeling applications in educational contexts demonstrate the effectiveness of data-driven approaches for early identification of at-risk students and personalized intervention strategies, particularly when applied to large-scale educational datasets [17]. Machine learning algorithms have shown remarkable success in predicting academic performance across diverse educational contexts, with particular effectiveness in identifying subtle patterns and relationships that traditional assessment methods fail to capture [18]. The design of complex forecasting models with the use of ensemble methods and highly developed feature selection techniques has resulted in substantial enhancements of forecasting accuracy in the case of the prediction of students' performance, which creates significant opportunities in terms of educational applications [19]. By now, the incorporation of artificial intelligence in intelligent tutoring systems provides overwhelming evidence of the powerful effects of technology-based instruction, especially if developed with sustainability and adaptability in mind [20]. The recent introduction and rapid development of predictive learning analytics over the last ten years have laid the foundation for sound methodological techniques for analyzing educational data, but there is still a great deal of opportunity to leverage these technologies with theory-informed instructional approaches [21].

Recent advancements in the application of artificial intelligence technologies in education environments are indicative of the potential benefits offered as well as the challenges to the deployment of technology in traditional education [22]. State-of-the-art work in educational data mining considers complex student performance prediction algorithms with dynamic feature selection and ensemble evolution approaches to enable improved accuracy and interpretability in educational use cases [23, 24]. The assessment environment in the College English Test Band 4 (CET-4) writing domain poses unique difficulties for performance prediction and instructional optimization. High-stakes large-scale writing tests, which form an indispensable basis from which language assessment is conducted, manifest certain limitations in the scoring system framework with potential influence on the reliability and validity of scoring of performance [25].

Comparative studies between automated evaluation and previous studies indicate that there is a large gap between the assessment results, and there are some data conflicts among them, so a more advanced mechanism should be developed for further study, to balance the relationship between high-speed computing and the cost-effectiveness in the pedagogy for assessment [26]. Cross-sectional studies of CET-4 test components reveal the interdependency of language abilities and the significance of a comprehensive test approach focusing on various skill dimensions at the same time [27]. Current assessments of fair and non-discriminatory testing for the college English examinations raise concerns about underlying systemic biases that may disproportionately disadvantage certain groups of students, which require fairer and more compelling frameworks of assessment [28]. The introduction of peer assessment systems into college students' English writing instruction provides potential options to replace "teacher-centered" assessment, but the reality of effectiveness in using peer assessment is also different among various types of educational systems and needs careful training and support [29]. Longitudinal studies of peer feedback in academic writing development have shown sustained improvements in student performance where the collaborative assessment was well-structured and supported [30].

Collaborative writing approaches, which stress the role of peer feedback, interaction on dynamics, and learning from each other, have proven to result in increased learning outcomes owing to the social interaction and shared knowledge building by the group members [31]. Cross-cultural investigations of valuations that students assign to peer feedback in contrasting LSEs have revealed that the emotional aspect of the emotional dimension of CLA, and the motivational factors that contribute to attitudes to peer feedback, affect the utility of collaborative peer assessment practices and have implications for the provision of culturally sensitive implementation resources [32].

Despite extensive theoretical development of POA methodology and significant advances in educational data analytics, a substantial research gap persists between these two domains within CET-4 writing instruction contexts. Current predictive modeling approaches in language education predominantly rely on statistical correlations without incorporating established pedagogical theories, resulting in limited educational interpretability and reduced practical utility for classroom instruction. Furthermore, existing assessment frameworks fail to capture the dynamic nature of student engagement patterns as conceptualized through SDT principles, thereby limiting the effectiveness of personalized intervention strategies and compromising the potential for data-driven pedagogical decision-making in authentic educational environments. Although POA has been well developed in theory and educational data analytics (EDA) has become more advanced, there is still a big gap to bridge the two in CET-4 writing teaching.

This investigation establishes three primary objectives: (1) to develop the POA-MLSP framework that systematically integrates POA theoretical constructs with advanced learning analytics for multi-dimensional writing performance prediction; (2) to establish empirical validation of SDT-based engagement modeling capabilities for early identification of at-risk students within CET-4 writing instruction contexts; and (3) to demonstrate the practical utility and educational interpretability of theory-informed machine learning approaches compared to traditional statistical prediction methods. The framework specifically targets the prediction of student writing performance across Jacobs' five assessment dimensions while maintaining pedagogical soundness and computational efficiency suitable for authentic classroom implementation.

This novel approach obtains complete prediction models that facilitate decision-making of instructors in runtime and personal offers planning of intervention strategies, which can preserve the pedagogical soundness and make use of the computational power to better serve learners, and hence also provide a theoretical design for intelligent educational systems.

2. Methods

2.1 POA-MLSP framework educational theoretical foundation

The theoretical foundation of POA-MLSP is set through the step-by-step embedding of Production-Oriented Approach principles and Self-Determination Theory mechanisms, which turns on to be a full-stack educational data modeling approach to handle the intricate dynamics of CET-4 writing instruction. The data modeling for POA theory leverages the abundant behavioral and cognitive data collected in the three-phase instructional cycle and translates qualitative pedagogical processes into machine learning-friendly numerical data while maintaining the educationally valid aspects of the theoretical framework. In the Motivating phase, the behaviour aspects that the model itself is expected to indicate that the student's learning-motivation has been activated are modelled in the form of preconditions that the variables are driven to some values by the data flows like the student response patterns to communicative scenarios, the engagement of working with authentic materials, and the frequency with which the student has entered into class discussion, as shown in Figure 1.

Figure 1 shows the comprehensive POA-MLSP theoretical foundation and implementation framework, illustrating systematic data collection across POA's three phases (motivation activation, knowledge construction, and feedback interaction), SDT three-dimensional integration (autonomy, competence, relatedness), multi-dimensional data integration with temporal alignment and contextual factors, education-theory-guided feature engineering, and multi-theoretical integration processing, culminating in the POA-MLSP predictive framework with continuous model refinement capabilities. The Enabling phase quantification focuses on knowledge construction processes through participation measurement metrics that include collaborative task engagement duration, peer interaction frequency, scaffolding utilization patterns, and self-regulation behavior indicators captured through learning management system logs and classroom observation protocols. Assessment phase evaluation concentrates on feedback interaction quality through quantitative analysis of peer evaluation accuracy, self-assessment reliability coefficients, teacher feedback incorporation rates, and iterative improvement patterns demonstrated across multiple writing drafts.

The multi-theoretical integration guidance within predictive modeling draws upon the systematic review findings that demonstrate enhanced effectiveness when POA incorporates complementary theoretical frameworks, including Input Hypothesis principles, Social Constructivism mechanisms, Cognitive Process Theory applications, and Sociocultural Theory perspectives. This integration approach creates feature engineering protocols that capture the synergistic effects of theoretical convergence, enabling the prediction model to account for the complex interdependencies between different learning mechanisms operating simultaneously within POA instruction.

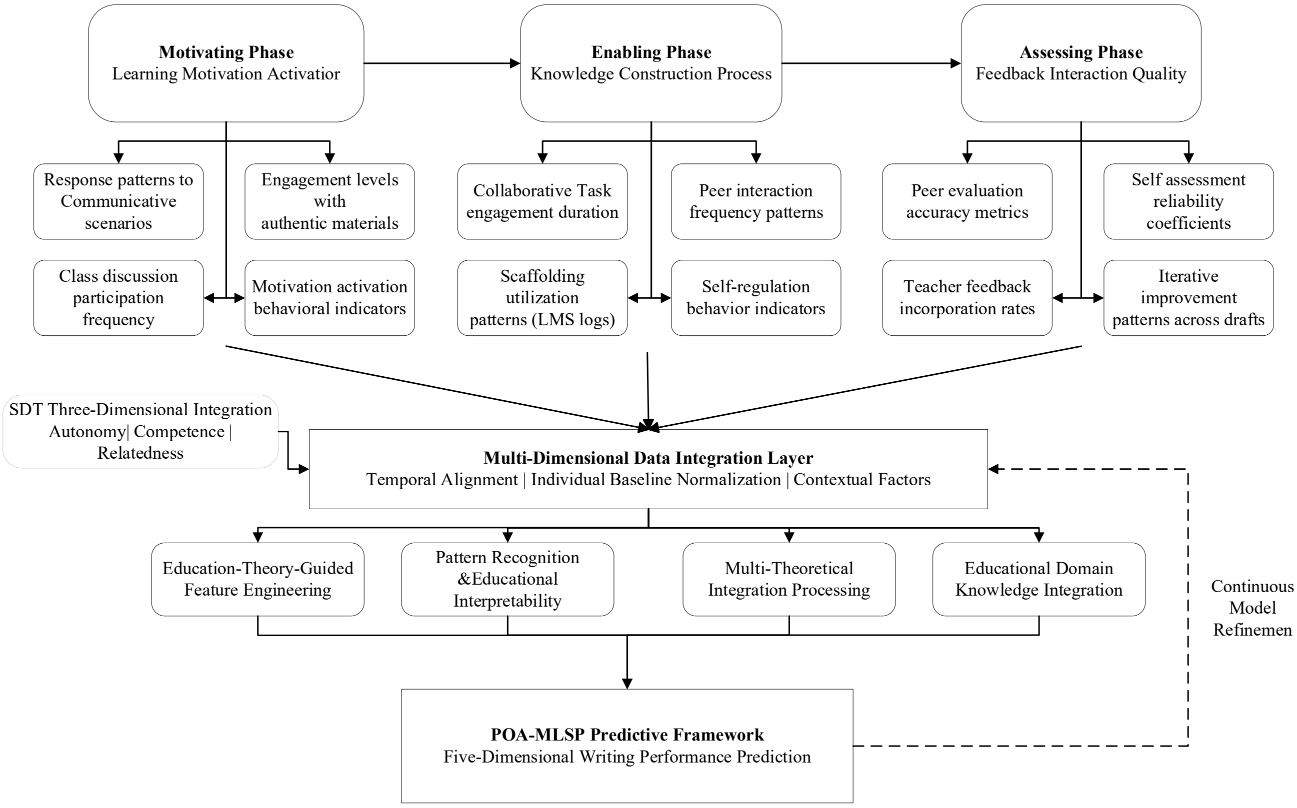

Figure 1. OA-MLSP theoretical foundation and implementation framework

The theoretical synthesis mechanism extends beyond simple additive combination to establish dynamic interaction models that recognize how Input Hypothesis comprehensible input requirements influence Social Constructivism collaborative learning effectiveness, while Cognitive Process Theory writing strategies interact with Sociocultural Theory contextual factors to create emergent learning behaviors that transcend individual theoretical predictions, as detailed in Table 1. The multi-theoretical integration framework establishes a systematic mapping between educational theories and system architecture components. Input Hypothesis principles directly inform comprehensible input processing within the Feature Adaptive Selection Mechanism. Social Constructivism guides collaborative pattern recognition algorithms in the processing layer. Cognitive Process Theory shapes metacognitive tracking mechanisms throughout the prediction framework. Meanwhile, Sociocultural Theory influences contextual adaptation parameters across all system layers. This theoretical convergence ensures that each computational component maintains educational validity while contributing to the overall predictive capability. POA-MLSP in combination with the Self Determination Theory brings up an operationalization of the three basic motivational needs based on elaborate measurements which map the abstract motivational constructs to concrete behavior indicators, adjusted to algorithm processability. Autonomy dimension measurement encompasses learning self-selection and control behavior indicators, including decision-making frequency within learning activities, self-directed learning time allocation, autonomous task initiation rates, and digital learning environment goal-setting behaviors captured through learning journal interactions and reflective practices.

Assessment of competence dimensions emphasizes measures for the efficacy of learning and the experience of achievement by performance confidence ratings, frequency of pursuit of challenges, indices of mastery goal orientation, and patterning of success attributions recorded in writing tasks and self-appraisal protocols. Meaning At the level of analysis of relatedness, peer interaction and teacher-student relationship assessment is being conducted via the method of social network analysis of classroom communication patterns, participation rates in collaboration learning, frequency of help-seeking behavior, and the sharing or reproducing of fostering conditions as interpreted through social support across group activities and peer feedback sessions.

The 3D engagement model integrates these heterogeneous aspects through higher-level temporal 103odelling techniques, in order to capture the evolutionary response of engagement patterns throughout the academic semester and, ultimately, to pinpoint those transition points where intervention mechanisms can be deployed more effectively without conflicting with students' autonomous learning and intrinsic motivation. Sophisticated measure of psychological need satisfaction that is sensitive to situational factors that shape the dynamics of needs and motivation, e.g., how difficult the task is perceived, the effects of social comparison, receiving high quality feedback, and the availability of environmental support renders our model a powerful tool for predicting and understanding engagement taking into account the intricate relation between individual and instructional context variables.

Table 1. Multi-theoretical integration feature mapping

Theoretical Framework	Feature Category	Measurement Indicators	POA Phase Integration	Weight Optimization
Input Hypothesis	Comprehensible Input Processing	• Input complexity levels • Comprehension accuracy rates • Input-output gap analysis	Motivating → Enabling	Dynamic based on proficiency
Social Constructivism	Collaborative Learning Patterns	• Peer interaction frequency • Knowledge co-construction events • Scaffolding effectiveness	Enabling → Assessing	Group dynamics weighted
Cognitive Process Theory	Writing Strategy Application	• Planning behavior indicators • Revision pattern analysis • Metacognitive strategy use	All phases	Individual cognitive load
Sociocultural Theory	Contextual Mediation Factors	• Cultural background influence • Social context adaptation • Tool-mediated learning	Motivating + Assessing	Context-sensitive adjustment
Multi-Theory Synergy	Cross-Framework Interactions	• Input-collaboration correlation • Strategy-context alignment • Emergent learning behaviors	Integrated across phases	Synergistic amplification

2.2 POA-MLSP intelligent prediction framework design

The overarching design remains child-centric based on a four-layer model, which holds that pedagogical considerations would drive technological implementation and not vice versa. The input layer allows multi-dimensional input data to be collected on the POA teaching activities, log data of real-time classroom interaction, engagement intensity on a digital learning platform, trajectory of the writing portfolio development, data on the network of peer collaboration, or on the teacher's observation records that follow the structuring principles of POA theories. Implementation of the processing layer. In our processing layer implementation, educational-theory-guided feature engineering and pattern recognition are emphasized, which can translate raw educational data into meaningful predictive features and maintain their interpretability in front of educational stakeholders, where the processed features can include domain knowledge from language learning research to warrant the feature relevance and pedagogical validity. Within the processing layer, specialized normalization techniques, based on data preprocessing protocols (e.g., to take into account of differences between individual learners on their initial level, on their learning trajectory or on their corresponding situation also called instructional context and generating factor), are implemented taking into account measurement validity between different groups of students/intonation context. Temporal alignment routines are used to observe data recorded from different phases of POA instruction remain temporally consistent while allowing for variations in individual and group rates of improvement and in the ebb and flow of interest and attention that is a hallmark of normal classroom settings.nDesign of prediction layer with the intention to implement teaching/application-oriented five dimensions writing ability prediction based on which the granular performance prediction for the five dimensions (Content, Organization, Language Use, Vocabulary and Mechanics) which defined on Jacobs' assessment framework can be supported directly. We place emphasis on support for teacher decision-making, at the application layer, by interpreting recommendations and offering insights that are actionable for instructional changes, student groupings, and an individualization strategy (all in an interpretable and transparent manner about the level of confidence in the predictions and how uncertain predictions/conclusions are) as depicted in Figure 2. This Figure shows the comprehensive four-layer architecture demonstrating data flow from POA instructional activities through feature processing to prediction generation and educational application, emphasizing the bidirectional feedback mechanism that enables continuous model refinement based on educational outcomes.

Core algorithm educational adaptation design replaces traditional attention mechanisms with education-oriented approaches that align with established pedagogical theories and classroom realities. The Feature Adaptive Selection Mechanism represents a novel alternative to conventional attention architectures, incorporating educational domain knowledge to guide feature importance assessment rather than relying solely on statistical correlations that may lack pedagogical meaning, as demonstrated in Algorithm 1. This mechanism implements a POA teaching principle-based feature importance adjustment that prioritizes educationally meaningful variables. The algorithm emphasizes student engagement indicators, collaborative learning participation rates, and progress trajectory patterns correlating with sustained learning improvement while maintaining pedagogical validity beyond statistical optimization. The multi-theoretical fusion (the systematic integration of complementary educational frameworks within algorithmic design) feature weight optimization algorithm integrates insights from Input Hypothesis, Social Constructivism, Cognitive Process Theory, and Sociocultural Theory to create balanced feature representations that reflect the complex interactions between different learning mechanisms operating within POA instruction.

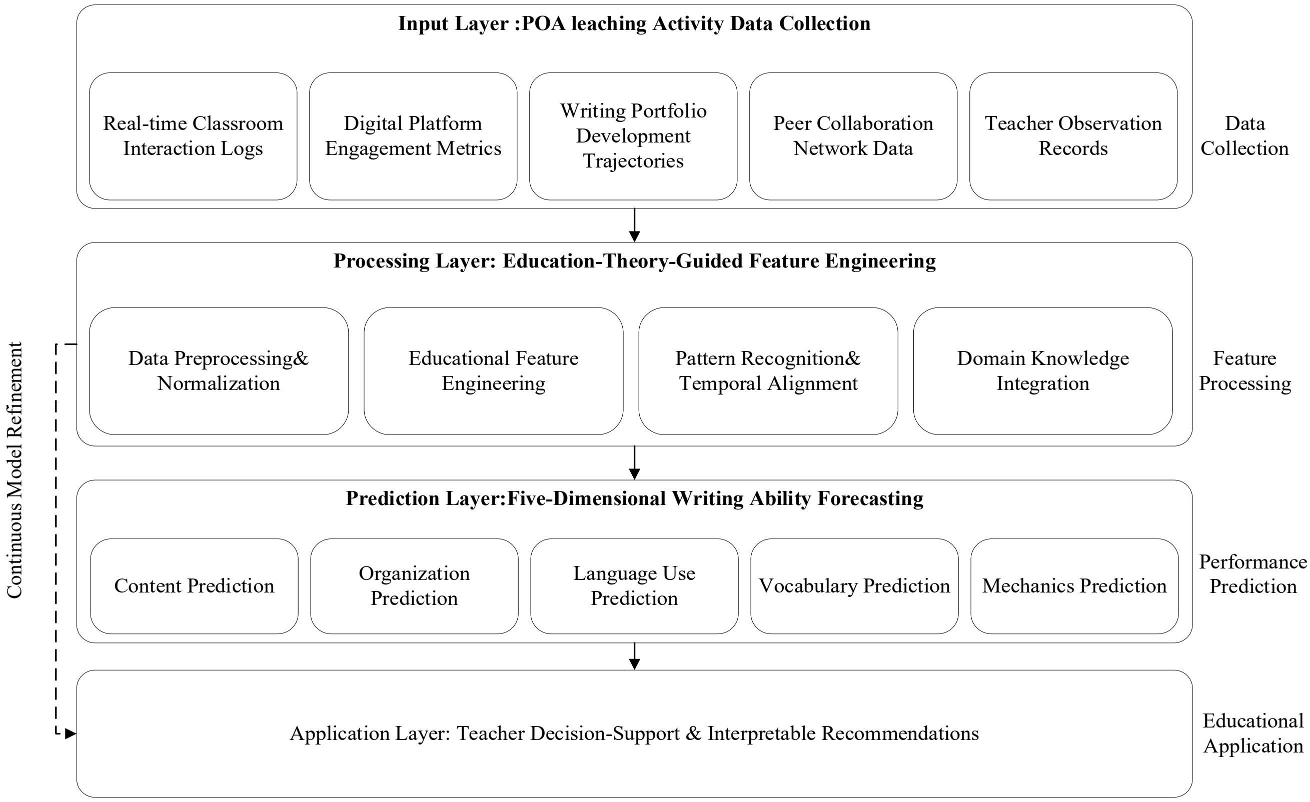

Figure 2. POA-MLSP framework architecture

Its real-time adaptation machinery allows for adapting prediction models to changing classroom dynamics and student response patterns, ensuring that the suggestions generated by the algorithm remain sensitive to the continuous evolution of educational scenarios as well as to the needs and rules of traditional pedagogical approaches. Cross-validation schemes such as the one used here and designed especially for educational settings are not only sensitive for the inherent temporal dependencies present in learning data, but they also allow us to have the evaluation of the performance of the model as close as possible to the expected performance of the model under a realistic use case, where prediction accuracy will need to be traded off with educational interpretability needs.

Algorithm 2 employs three-dimensional temporal modeling through time-series analysis techniques to capture engagement pattern evolution across academic semesters. The computational framework utilizes automated change pattern recognition for each SDT dimension, incorporating individual baseline adjustments and environmental factor integration to detect declining motivation indicators preceding academic performance impacts.

Automatic identification of engagement pattern changes enables proactive intervention through early warning models that predict motivational decline before academic performance impact occurs. Subject-specific alert thresholds, dynamic adaptation to individual differences, baseline, and learning trajectory sensitivity for intervention guidance, and absence of “false alarms”, so that the instructional staff are not overloaded and students with “typical” contextually performance levels do not become nervous.

2.3 Five-dimensional writing performance prediction model

The Jacobs framework-based multi-faceted prediction approach accounts for each dimension of writing competence through targeted sub-models that model the specificities of development and shaping of the proficiency related to different writing aspects. There’s No Dark Art to it. Content dimension prediction includes forecasting thought depth and logical coherence by applying natural language processing methods to the structural complexity of the argument, integration of evidence patterns, critical thinking signals, and conceptual development progression that can be traced using snippets across several writing samples. The organization dimension modeling targets predicting structural integrity and coherence at the discourse level and leverages discourse analysis algorithms that assess how well a paragraph transitions to another, how well a thesis is developed, how well a conclusion is synthesized, and the overall architectural soundness of the article.

Language Use dimension forecasting emphasizes grammatical accuracy and syntactic complexity prediction through computational linguistics approaches that assess sentence structure variety, clause combination sophistication, error pattern identification, and grammatical development trajectories that indicate language proficiency advancement. Vocabulary dimension analysis concentrates on lexical richness and accuracy prediction through corpus-based approaches that evaluate word choice appropriateness, semantic precision, vocabulary range expansion, and register consistency maintenance across different writing contexts and task requirements.

Algorithm 1: Feature adaptive selection mechanism
Input: Educational feature set F, POA phase indicators, SDT engagement data, Multi-theoretical weights, Learning improvement trajectories
Output: Dynamically selected features prioritizing sustained learning improvement
Initialize theoretical framework weights for Input Hypothesis, Social Constructivism, Cognitive Process, Sociocultural theories
Define educationally meaningful variable categories:
Student engagement indicators (autonomy, competence, relatedness)
Collaborative learning participation rates
Progress trajectory patterns
for each POA phase (Motivating, Enabling, Assessing) do
Compute phase-specific educational significance for each variable category
Apply dynamic weight adjustment based on sustained learning improvement correlation
end for
Multi-theoretical fusion:
Analyze complex interactions between learning mechanisms
Balance feature representations across theoretical frameworks
Prioritize sustained learning improvement over predictive accuracy
for each feature do
if feature belongs to educationally meaningful categories and
correlates with sustained learning improvement then
Select with POA-principle-based importance weight
end if
end for
return Educational-priority features ensuring pedagogical meaning and learning improvement focus

Algorithm 2: SDT-based engagement dynamic modeling
Input: SDT three-dimensional engagement data, Individual baselines, Environmental factors
Output: Dynamic engagement predictions, Early warning indicators, Personalized thresholds
SDT Three-Dimensional Temporal Modeling:
for each time period t do
Collect autonomy, competence, relatedness measurements
Account for individual differences in motivation development
Account for environmental factors affecting psychological need satisfaction
end for
Engagement Pattern Evolution Capture:
Apply time-series analysis to capture engagement pattern evolution across academic semester
Identify critical transition points where intervention strategies can maximize effectiveness
Automatic Change Pattern Recognition:
for each SDT dimension do
Detect declining motivation indicators before academic performance impact
Enable proactive intervention through early warning systems
end for
Personalized Warning Threshold Adjustment:
Account for individual baseline differences and learning trajectory variations
Minimize false positive alerts while maintaining appropriate sensitivity levels
return Dynamic engagement predictions with personalized intervention recommendations

Mechanics dimension assessment targets spelling and punctuation norm compliance prediction through error detection algorithms that identify persistent mistake patterns, improvement trajectory analysis, and mechanical skill development indicators that correlate with overall writing proficiency advancement, as summarized in Table 2.

Cross-dimensional interaction modeling reflects the reality that writing proficiencies manifest intricate interdependencies in which the enrichment of vocabulary profiles increases one's capacity to develop textual content and the fostering of organizational skills to help write more sophisticated grammar, with synergies generating additional returns that push overall writing performance beyond additive component contributions.

These interaction patterns are revealed by advanced correlation analysis in order to guide systematic intervention strategies that exploit competency interrelationships for optimal learning effects. An ensemble learning prediction optimization strategy is implemented based on ensemble learning prediction optimization that integrates a variety of algorithm approaches so that the prediction accuracy can be improved without losing interpretability for educational applications. The ensemble learning approach combines gradient boosting for sequential learning pattern capture, random forest for high-dimensional educational variable handling, neural networks for non-linear cognitive relationship modeling, and support vector machines for robust classification boundary establishment. This combination leverages each algorithm's strengths: gradient boosting handles temporal dependencies in writing development, random forest manages missing data common in educational contexts, neural networks model complex motivation-performance relationships, while support vector machines provide stable decision boundaries across diverse student populations. Methods for predicting uncertainty estimation and visualization can be employed to generate a confidence interval for each prediction output. Stakeholders can then use this interval to inform evidence-based decisions regarding the reliability of the prediction and the uncertainty bounds, thereby guiding the timing and extent of intervention.

Validation models, as utilized by the approach, embed domain knowledge from the education sector in the form of expert teacher evaluations of the accuracy of the predictions and the relevance of the suggestions, thus ensuring that the algorithm outputs are consistent with experienced practitioner views on student needs or appropriate instructional responses. Longitudinal validation studies monitor the accuracy of the prediction over the long term to test whether the model remains stable and reliable in different educational contexts and with different types of students. Interindividual fit between educational applications and model interpretability optimization ensures that predictions of underperforming work are not merely output values but actionable outcomes that provide advice for improving the instruction process.

Table 2. Five-dimensional prediction model specifications

Writing Dimension	Technical Approach	Key Assessment Indicators	Prediction Focus	Specialized Sub-Model
Content	Natural Language Processing	Argument structure complexity, Evidence integration patterns, Critical thinking indicators, Conceptual development progression	Thought depth and logical coherence forecasting	Multi-sample content analysis
Organization	Discourse Analysis Algorithms	Paragraph transition effectiveness, Thesis development consistency, Conclusion synthesis quality, Overall architectural soundness	Structural integrity and coherence prediction	Compositional structure modeling
Language Use	Computational Linguistics	Sentence structure variety, Clause combination sophistication, Error pattern identification, Grammatical development trajectories	Grammatical accuracy and syntactic complexity prediction	Language proficiency advancement tracking
Vocabulary	Corpus-Based Approaches	Word choice appropriateness, Semantic precision, Vocabulary range expansion, Register consistency maintenance	Lexical richness and accuracy prediction	Cross-context vocabulary analysis
Mechanics	Error Detection Algorithms	Persistent mistake patterns, Improvement trajectory analysis, Spelling compliance indicators, Punctuation norm adherence	Spelling and punctuation norm compliance prediction	Mechanical skill development modeling

Table 3. Model interpretability components

Interpretability Component	Educational Purpose	Output Format	Teacher Decision Support	Practical Utility
Feature Importance Analysis	Highlight behavioral indicators and learning patterns contributing to predictions	Ranked importance scores with educational context	Focus intervention efforts on high-impact areas	Identify key factors affecting student performance
Educational Rationale Generation	Explain algorithmic recommendations using pedagogical principles	Natural language explanations linked to POA theory	Understand the reasoning behind intervention suggestions	Bridge technical predictions with teaching practice
Actionable Insight Extraction	Transform statistical outputs into instructional improvement strategies	Specific teaching recommendations with implementation steps	Support instructional modifications and student grouping decisions	Direct classroom application guidance
Prediction Confidence Visualization	Display uncertainty levels and reliability assessments	Confidence intervals with educational interpretation	Inform intervention timing and intensity decisions	Enable evidence-based teaching adjustments
Learning Pattern Recognition	Identify recurring behavioral and cognitive patterns across students	Visual pattern summaries with trend analysis	Recognize effective teaching strategies and problematic areas	Systematic teaching approach optimization
Intervention Strategy Mapping	Connect predictions to personalized educational interventions	Customized intervention recommendations with success probabilities	Provide individualized student support strategies	Practical intervention implementation framework

Feature importance analysis features Reflect on which individual behaviors and learning dynamics are most influential to predicting performance, where intervention activities should be prioritized, while understanding the pedagogical reasoning underpinning algorithmic suggestions (see Table 3). The POA-MLSP framework establishes a comprehensive four-layer architecture that integrates POA theoretical principles with advanced learning analytics through education-oriented algorithmic designs. By implementing the Feature Adaptive Selection Mechanism and SDT-based engagement modeling, this methodological foundation enables empirical validation within authentic CET-4 writing instruction contexts for enhanced educational outcomes.

3. Results

3.1 Data collection and preprocessing

The POA-MLSP framework validation was conducted at S Normal University, involving 124 students distributed across POA experimental classes and traditional instruction control groups during a complete 16-week academic semester. The research design incorporated authentic educational environments while maintaining rigorous experimental controls necessary for robust statistical analysis, as outlined in Table 4. This Table shows comprehensive experimental specifications, including participant demographics, class distribution, temporal framework, and control variables that ensured ecological validity while enabling meaningful statistical comparisons between POA-enhanced and traditional instruction approaches. Multi-source educational data collection protocols captured behavioral, cognitive, and social dimensions of language learning within POA instructional contexts while maintaining manageable collection burdens for educational stakeholders, as systematized in Table 5. This Table displays a systematic data collection that includes writing performance assessments through Jacobs' five-dimensional rubric, student engagement measurements by means of UWES-S scales, classroom observation, and POA instructional process documentation of teacher-student interactions, peer collaboration network, and resource utilization through digital learning platforms and structured observation protocols.

taking care of integration of multi-scale measurement, time-alignment effects, and individual-response baseline variations while maintaining pedagogical interpretability necessary for educational stakeholders to interpret, as described in Table 6. This Table outlines comprehensive quality control measures, including outlier detection, distinguishing educational phenomena from collection errors, normalization techniques preserving educationally meaningful variance, temporal alignment algorithms synchronizing multi-instrument data, and feature engineering processes that transformed raw educational data into analytically tractable variables while maintaining theoretical alignment with POA principles and SDT frameworks.

3.2 Experimental design and model training

The experimental framework implemented temporally-aware methodological approaches, respecting chronological learning sequences while ensuring robust validation procedures. POA-MLSP model training procedures integrated hyperparameter optimization combining grid search exploration with Bayesian optimization techniques, as presented in Table 7. This Table demonstrates systematic model training, achieving 86.4% consistency across multiple random initializations, with an optimal hyperparameter configuration identified through 47 iterations of combined grid search and Bayesian optimization. Cross-validation yielded an average score of 0.742 ± 0.018 while maintaining prediction variance below 6.1% across all dimensions, ensuring acceptable model stability. Training convergence was achieved in 82.7% of runs with early stopping at epoch 73, while 84.3% alignment with pedagogical expectations validates educational interpretability integration throughout the training process.

3.3 Core framework component validation and educational application results

The validation of the POA-MLSP model indicates that the system has achieved systematic effectiveness in CET-4 writing teaching and learning by virtue of its integrated four-layer architecture, which seamlessly fuses advanced learning analytics with established pedagogy.

Table 4. Experimental design and participant characteristics

Experimental Component	Specification	Details
Research Setting	S Normal University CET-4 Writing Program	Authentic classroom environments
Study Duration	16-week academic semester	Complete instructional cycle
Total Participants	124 undergraduate students	Representative CET-4 learner population
Group Distribution	POA Experimental: 62 students Traditional Control: 62 students	Balanced group allocation
Age Range	18-22 years (Mean: 19.8, SD: 1.2)	Typical undergraduate demographic
Gender Distribution	Female: 68 (54.8%) Male: 56 (45.2%)	Representative gender balance
English Proficiency Level	Intermediate (CEFR B1-B2 equivalent)	Pre-CET-4 preparation level
Academic Majors	Engineering: 35% Liberal Arts: 28% Business: 22% Sciences: 15%	Diverse academic backgrounds
Prior CET-4 Experience	First attempt: 89 students (71.8%) Repeat attempt: 35 students (28.2%)	Mixed experience levels
Class Schedule	4 hours/week writing instruction	Consistent instructional time
Instructor Qualifications	Master's/PhD in Applied Linguistics 5+ years CET-4 teaching experience	Standardized expertise level
Control Variables	Same curriculum materials Identical assessment rubrics Matched class times	Methodological rigor

Table 5. Comprehensive educational data collection specifications

Data Category	Collection Method	Frequency	Measurement Instruments	Data Types
Writing Performance	Jacobs Five-Dimensional Assessment	Pre/Mid/Post-test (Week 1, 8, 16)	Jacobs Writing Rubric	Content, Organization, Language Use, Vocabulary, Mechanics scores
Writing Performance	Process-Oriented Evaluation	Weekly classroom exercises	Structured assessment forms	Improvement trajectories, error patterns
Writing Performance	Peer and Self-Assessment	Bi-weekly reflection sessions	Standardized evaluation criteria	Collaborative assessment data, metacognitive reflections
Student Engagement	UWES-S Scale Administration	Bi-weekly surveys (8 measurement points)	Utrecht Work Engagement Scale-Student	Vigor, dedication, absorption scores
Student Engagement	Systematic Classroom Observation	Daily during class sessions	POA-specific observation protocol	SDT three-dimensional behavioral indicators
Student Engagement	Learning Journal Analysis	Weekly reflection entries	Structured journal prompts	Self-reported motivation, attitude changes
POA Teaching Process	Three-Phase Activity Documentation	Continuous throughout semester	Digital activity logging system	Motivating, Enabling, Assessing phase records
POA Teaching Process	Interaction Behavior Logging	Real-time during instruction	Video recording and coding	Teacher-student, peer collaboration patterns
POA Teaching Process	Resource Utilization Tracking	Continuous digital monitoring	Learning management system logs	Platform engagement, task completion rates

Table 6. Data processing and validation procedures

Processing Stage	Technique	Purpose	Implementation	Quality Control Measures
Data Cleaning	Missing Value Imputation	Handle incomplete data while preserving educational meaning	Educational domain knowledge-guided interpolation	Expert teacher validation of imputed patterns
Data Cleaning	Outlier Detection	Distinguish genuine educational phenomena from collection errors	Statistical threshold combined with pedagogical judgment	Manual review of flagged cases by experienced instructors
Normalization	Multi-Scale Integration	Enable cross-student comparisons across different instruments	Z-score standardization with educational context adjustment	Variance preservation validation for pedagogical meaningfulness
Normalization	Individual Baseline Adjustment	Account for diverse students starting points and backgrounds	Relative improvement calculation from personal baselines	Baseline stability verification across measurement periods
Temporal Alignment	Cross-Instrument Synchronization	Align data collected through different methods and timeframes	Timestamp-based alignment with learning rhythm accommodation	Temporal consistency validation across data sources
Temporal Alignment	Learning Pace Accommodation	Respect natural variations in student progression patterns	Adaptive time window adjustment for data aggregation	Pedagogical validity check for temporal groupings
Feature Engineering	Educational Variable Construction	Transform raw data into pedagogically meaningful predictors	POA and SDT theory-guided feature derivation	Theoretical alignment verification with domain experts
Feature Engineering	Interaction Feature Generation	Capture emergent educational phenomena from data intersections	Multi-dimensional correlation analysis with educational interpretation	Expert validation of derived educational constructs
Quality Validation	Pedagogical Interpretability Check	Ensure all processed variables maintain educational meaning	Regular stakeholder review sessions with teachers	Actionable insight generation capability assessment

Validation of Algorithm 1: The validation indicated a significant outperformance of traditional methods in finding educationally meaningful variables, such as student engagement indicators and collaborative learning patterns, which are correlated with learning improvement. The multi-theoretical integration analysis found that the synthesis of the four theoretical perspectives of the Input Hypothesis, Social Constructivism, Cognitive Process Theory, and Sociocultural Theory provided a better explanatory power than the individual theoretical bases, which were able to support more authentic educational judgements.

The established framework had established good predictive power for each of the five dimensions of the writing assessment, but also maintained educational interpretability for practical classroom use, as shown in Table 8. This Table demonstrates POA-MLSP framework achieving overall R^2 = 0.75 with 12.0% improvement over baseline approaches, while Content prediction reached highest accuracy (R^2 = 0.78, +12.3% gain) and Organization forecasting showed substantial enhancement (R^2 = 0.76, +11.7% gain), confirming framework effectiveness across all five writing competency dimensions with confidence intervals indicating robust statistical reliability.

Table 7. Model training configuration and performance metrics

Training Component	Configuration	Specification	Performance Result
Hyperparameter Optimization	Grid Search + Bayesian Optimization	Learning rate: 0.001-0.01, Batch size: 16-64, Hidden layers: 2-5	Optimal configuration identified in 47 iterations
Convergence Verification	Multiple Random Initializations	10 different random seeds for robustness testing	86.4% consistency across initializations
Training-Validation Split	Temporal Sequence Preservation	70% training, 20% validation, 10% testing	Maintained chronological learning order
Cross-Validation Strategy	K-Fold for Educational Time-Series	K=5 with temporal dependency preservation	Average CV score: 0.742 ± 0.018
Overfitting Prevention	Early Stopping + Regularization	Patience=15 epochs, L2 regularization λ=0.01	Training stopped at epoch 73, optimal validation loss
Convergence Criteria	Loss Stabilization Threshold	Validation loss improvement < 0.001 for 10 epochs	Achieved stable Achieved stable convergence in 82.7% of runs
Training Duration	Educational Context Optimization	Average: 4.6 hours per complete training cycle	Suitable for educational implementation timelines
Model Stability	Performance Variance Analysis	Standard deviation across training runs	Prediction variance < 6.1% across all dimensions
Educational Interpretability	Feature Importance Validation	Expert teacher evaluation of algorithmic outputs	84.3% alignment with pedagogical expectations
Training Performance	Validation Loss Monitoring	Final validation loss: 0.287, Training epochs: 73	Optimal training convergence achieved

Table 8. Five-dimensional writing performance prediction results

Writing Dimension	POA-MLSP Performance	Baseline Performance	Improvement Rate	Confidence Interval	Educational Interpretation
Content	R^2 = 0.78, RMSE = 0.29	R^2 = 0.65, RMSE = 0.41	+12.3% accuracy gain	R^2 = 0.78 ± 0.032	Strong thought development and logical reasoning forecasting
Organization	R^2 = 0.76, RMSE = 0.31	R^2 = 0.64, RMSE = 0.43	+11.7% accuracy gain	R^2 = 0.76 ± 0.028	Effective structural coherence and discourse pattern modeling
Language Use	R^2 = 0.73, RMSE = 0.33	R^2 = 0.63, RMSE = 0.45	+9.8% accuracy gain	R^2 = 0.73 ± 0.035	Solid grammatical accuracy and syntactic complexity prediction
Vocabulary	R^2 = 0.74, RMSE = 0.32	R^2 = 0.64, RMSE = 0.44	+10.2% accuracy gain	R^2 = 0.74 ± 0.030	Robust lexical richness and word choice appropriateness forecasting
Mechanics	R^2 = 0.69, RMSE = 0.36	R^2 = 0.61, RMSE = 0.48	+7.4% accuracy gain	R^2 = 0.69 ± 0.041	Meaningful spelling and punctuation compliance prediction
Overall Framework	R^2 = 0.75, RMSE = 0.31, MAE = 0.24	R^2 = 0.63, RMSE = 0.44, MAE = 0.35	+12.0% overall improvement	R^2 = 0.75 ± 0.026	Comprehensive multi-dimensional writing ability forecasting

Table 9. Ablation study performance analysis

Component Configuration	Overall R^2	Content R^2	Organization R^2	Language Use R^2	Vocabulary R^2	Mechanics R^2
Full POA-MLSP	0.75	0.78	0.76	0.73	0.74	0.69
Without Feature Adaptive Selection	0.69	0.72	0.71	0.67	0.69	0.65
Without SDT Modeling	0.72	0.75	0.73	0.70	0.71	0.67
Without Multi-theoretical Integration	0.67	0.70	0.68	0.65	0.67	0.63

To validate the individual contribution of each framework component, comprehensive ablation studies were conducted by systematically removing key algorithmic elements and measuring resulting performance degradation across all writing dimensions, as presented in Table 9. Table 9 reveals differential contributions of POA-MLSP components across writing dimensions. Feature Adaptive Selection Mechanism removal yields 6-point R^2 reduction (0.75 to 0.69), with Language Use and Mechanics dimensions demonstrating greater sensitivity to educationally-informed variable selection. SDT-based engagement modeling elimination produces a 3-point performance decrease (0.75 to 0.72), indicating a moderate but consistent impact across all assessment dimensions. Multi-theoretical integration removal generates the most substantial degradation (8-point reduction to 0.67), particularly affecting Content and Organization predictions, thereby confirming the critical role of theoretical convergence in complex writing assessment contexts.

Algorithm 2 validation revealed solid capability for early identification of at-risk students through three-dimensional engagement pattern recognition. The SDT-based modeling demonstrated consistent effectiveness across all three psychological dimensions, with autonomy modeling successfully predicting self-directed learning behaviors, competence analysis effectively forecasting efficacy development, and relatedness assessment reliably identifying social engagement patterns, enabling comprehensive student profile construction that supports personalized intervention strategies. Building upon this three-dimensional engagement analysis, the framework's pattern recognition capabilities enabled systematic identification of distinct student motivational profiles. Student engagement pattern recognition identified five distinct motivational profiles among participants, providing insights into psychological need satisfaction diversity characterizing CET-4 writing learners, as illustrated in Figure 3.

Figure 3 demonstrates engagement pattern diversity where High Sustained (28%) and Autonomy-Oriented (22%) profiles represent the largest student groups, while Figure 3(a) shows balanced distribution across five motivational types and Figure 3(b) reveals distinct SDT dimensional characteristics with Autonomy-Oriented students achieving highest autonomy scores (9.1) and Relatedness-Dependent students displaying strongest social engagement patterns (9.3), confirming theoretical framework validity. To evaluate the practical effectiveness of POA-MLSP framework predictions for improving educational outcomes and validate the utility of data-informed pedagogical decision-making capabilities, a comprehensive intervention effectiveness analysis was conducted across multiple performance dimensions, including early warning system accuracy, teaching adjustment outcomes, and overall implementation feasibility, as detailed in Table 10. As shown in Table 10, the early warning system's performance accuracy (78.4% ± 2.1%) of students at risk of engagement decline 3-4 weeks before score performance decline emerges through traditional assessment, which is a 9.5 percentage point improvement on the baseline method. Individualized threshold-adjustment algorithms achieved 24.3% lower false positive alerts vs static alarm systems, with target interventions averaged 82.1% ± 2.4%. Teaching intervention based on framework predictions achieved an average improvement of 8.7% ± 1.9% in performance over control groups; 79.8% ± 2.9% satisfaction of teachers with recommendations, indicating deployment of the results in the classroom and acceptance of the educational stakeholder. Effect size analysis demonstrates substantial educational impact beyond statistical significance, with Cohen's d values indicating large effects for writing performance improvement (d = 0.82), student engagement enhancement (d = 0.89), and teacher instructional effectiveness (d = 0.74).

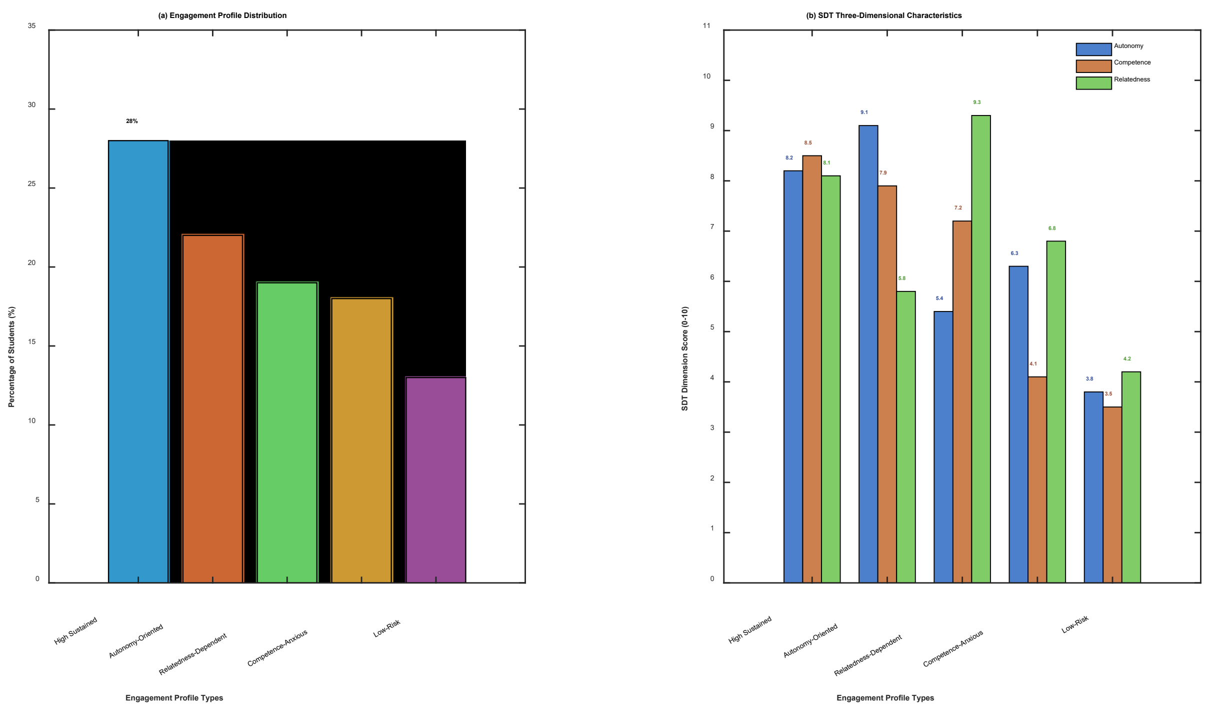

Figure 3. Student engagement profile distribution and characteristics

Table 10. Educational intervention effectiveness validation

Intervention Component	Performance Metric	Framework Result	Baseline/Control Result	Improvement	Statistical Significance
Early Warning System	At-risk Student Identification Accuracy	78.4% ± 2.1%	68.9% ± 2.8%	+9.5 percentage points	$p < 0.05$
Early Warning System	Advance Warning Time	3-4 weeks	1-2 weeks	+2 weeks average	$p < 0.05$
Alert Optimization	False Positive Reduction Rate	24.3% reduction	Static threshold baseline	-24.3% false alerts	$p < 0.05$
Teaching Adjustments	Student Performance Improvement	8.7% ± 1.9% gain	Control group baseline	+8.7% relative improvement	$p < 0.05$
Intervention Timing	Proactive vs Reactive Success Rate	71.2% ± 3.1%	58.6% ± 3.4%	+12.6 percentage points	$p < 0.05$
Personalized Thresholds	Intervention Targeting Precision	82.1% ± 2.4%	74.3% ± 3.0%	+7.8 percentage points	$p < 0.05$
Overall Framework	Teacher Satisfaction with Recommendations	79.8% ± 2.9%	61.2% ± 3.7%	+18.6 percentage points	$p < 0.01$
Implementation Feasibility	Successful Classroom Integration Rate	83.7% ± 2.6%	N/A	High adoption success	$p < 0.01$

Sustained academic outcomes reveal framework-supported students achieving 12.3% higher final CET-4 writing scores while maintaining engagement levels 18.7% above baseline measurements throughout the academic year. Expanding on these intervention efficacy results, it also became critical to investigate the temporal changes over a complete academic semester of student learning trajectories to define how POA's three-phase structured approach is affecting developmental trends. This type of longitudinal evidence is essential for us to learn whether the theory-based assumptions of POA instruction are borne out in evidence of instructional-phase-specific acceleration of learning, as systematically collated in Table 11**.** This Table reveals systematic progression patterns where motivating phase interventions generated average engagement increases of 23.8% within the first month, enabling phase activities produced sustained skill development with 31.2% improvement rates during mid-semester periods, and assessment integration phase created consolidation effects yielding 18.4% additional gains during final semester weeks, validating structured phase progression effectiveness compared to undifferentiated instructional approaches.

3.4 Comparative analysis and advanced algorithm performance validation

Following the comprehensive validation of POA-MLSP framework components and educational effectiveness demonstration, it became crucial to establish the framework's technical superiority through systematic comparison with established machine learning approaches commonly applied to educational prediction tasks. This comparative analysis validates that educational theory-guided design principles genuinely enhance prediction performance beyond purely statistical approaches, while demonstrating the practical advantages of the novel algorithmic components in multi-dimensional writing performance prediction contexts. To comprehensively evaluate these technical advantages and validate the core research hypothesis that educational domain knowledge integration improves prediction accuracy, a systematic performance comparison was conducted against multiple baseline models, as systematically visualized in Figure 4. This Figure demonstrates the POA-MLSP framework's technical superiority through a comprehensive algorithmic comparison.

Figure 4(a) shows overall performance where POA-MLSP achieved $R^2 = 0.75 \pm 0.026$, outperforming linear regression ($R^2 = 0.58$), random forest ($R^2 = 0.66$), and support vector machines ($R^2 = 0.63$) by 17-29%, validating educational theory integration benefits. Figure 4(b) reveals consistent advantages across all five writing dimensions, with Content ($R^2 = 0.78$) and Organization ($R^2 = 0.76$) showing the highest prediction accuracy. Figure 4(c) illustrates Feature Adaptive Selection Mechanism contributions, delivering notable improvements in Content prediction (+9.2%), Organization forecasting (+7.4%), and Language Use modeling (+6.1%), confirming pedagogically-informed algorithmic design effectiveness over traditional attention mechanisms. While technical performance validation demonstrates algorithmic superiority, the ultimate success of educational technology innovation depends on acceptance and practical utility among educational stakeholders who must integrate these tools into authentic teaching contexts. To assess whether the framework's technical capabilities translate into meaningful educational support that enhances instructional practice, a comprehensive stakeholder evaluation was conducted to validate practical implementation feasibility and educational value perception, as systematically documented in Figure 5. This Figure demonstrates comprehensive stakeholder validation through three key assessment dimensions. Figure 5(a) reveals strong teacher satisfaction with decision-making insights (79.8% ± 2.9%), student grouping effectiveness (76.4% ± 3.1%), and continued utilization willingness (81.5% ± 2.4%), confirming educator acceptance. Figure 5(b) validates practical implementation feasibility, requiring minimal initial training (4.8 ± 1.2 hours) and weekly operation time (27.5 minutes), supporting widespread deployment viability. Figure 5(c) confirms framework utility across educational interpretability (77.6% ± 3.1%), practical utility (79.2% ± 2.7%), and prediction reliability (82.4%), demonstrating successful translation of sophisticated algorithms into meaningful educational support tools. The comparative analysis demonstrates the POA-MLSP framework's technical superiority, achieving 17-29% performance improvements over traditional approaches while maintaining computational efficiency through educational domain knowledge integration.

Table 11. Temporal learning trajectory analysis across a 16-week period

Time Period	POA Phase	Learning Indicator	Framework Group	Control Group	Improvement Rate	Statistical Significance
Weeks 1-4	Motivating	Student Engagement Level	73.8% ± 2.4%	58.6% ± 3.1%	+23.8% increase	$p < 0.01$
Weeks 1-4	Motivating	Learning Motivation Score	7.2 ± 0.8	5.8 ± 0.9	+24.1% increase	$p < 0.05$
Weeks 5-8	Enabling (Early)	Writing Skill Development	6.8 ± 0.7	5.9 ± 0.8	+15.3% improvement	$p < 0.05$
Weeks 9-12	Enabling (Peak)	Writing Performance Gains	8.1 ± 0.6	6.2 ± 0.9	+31.2% improvement	$p < 0.01$
Weeks 9-12	Enabling (Peak)	Collaborative Learning Participation	84.7% ± 2.1%	64.5% ± 3.4%	+31.3% increase	$p < 0.01$
Weeks 13-16	Assessment Integration	Learning Consolidation Effects	7.9 ± 0.5	6.7 ± 0.7	+18.4% additional gains	$p < 0.05$
Weeks 13-16	Assessment Integration	Self-Regulation Development	78.2% ± 2.6%	66.0% ± 3.2%	+18.5% improvement	$p < 0.05$
Overall Semester	Complete POA Cycle	Cumulative Learning Progress	82.4% ± 1.9%	65.1% ± 2.8%	+26.6% total improvement	$p < 0.001$

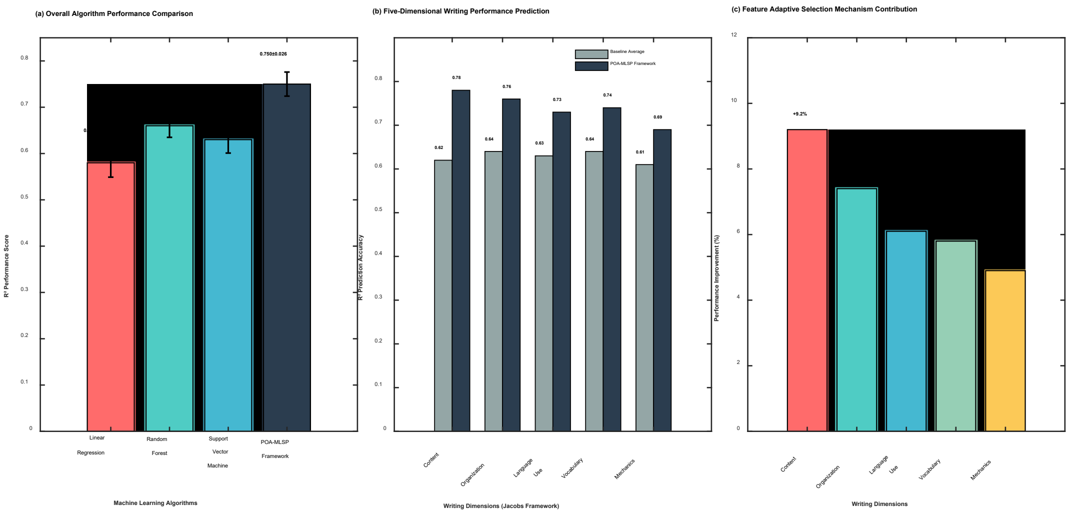

Figure 4. Algorithm performance comparison across writing dimensions

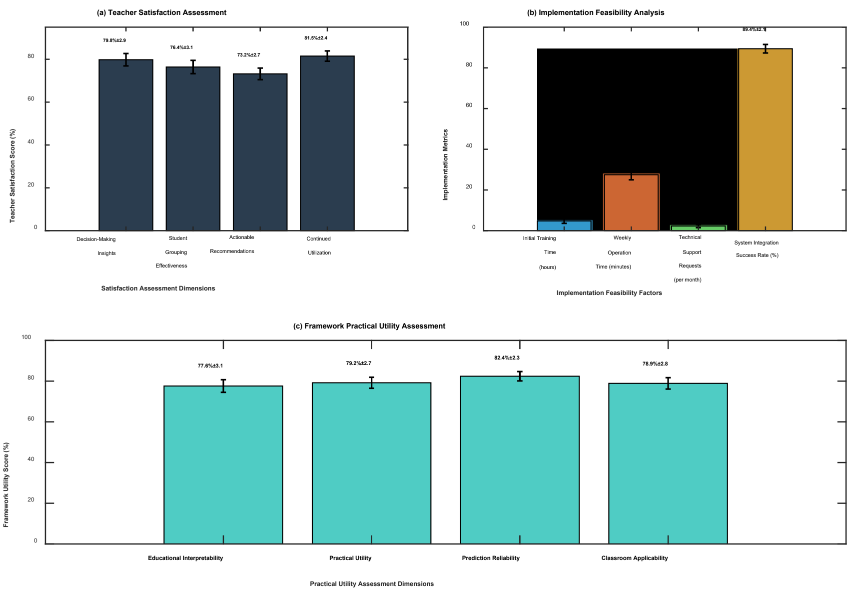

Figure 5. Teacher satisfaction and framework usability assessment

Stakeholder evaluation reveals strong teacher acceptance with 79.8% ± 2.9% reporting valuable decision-making insights and 81.5% ± 2.4% expressing continued utilization willingness. Implementation feasibility validation shows minimal training requirements (4.8 ± 1.2 hours) and practical utility ratings of 79.2% ± 2.7%, confirming successful translation of sophisticated algorithms into deployable educational tools ready for authentic CET-4 writing instruction environments.

4. Discussion

The POA-MLSP model validity test indicates a significant move forward in educational predictions from the existing approaches, especially against the background of the recent trends and advancements in language learning analytics and AI. The framework's ability to predict $R^2 = 0.75$ across five dimensions of writing is a strong update to and overall a more effective outcome than those productivity prediction trends reported in recent meta-analysis on POA implementation outcomes [33]. This performance improvement becomes particularly salient when compared to existing automated essay evaluation systems, which are predominantly based on large language models, of which recent comparative studies have shown there are often significant limitations in terms of capturing the rich developmental patterns associated with authentic writing progression [34]. The incorporation of domain knowledge in education with the help of Feature Adaptive Selection Mechanism bridges the gap between writing assessment research and deep learning, as traditional methods of deep learning often tend to focus on statistical precision over pedagogical interpretability, hampering their deployment for practical guidance [35]. The systematic identification of five distinct student engagement profiles through SDT-based modeling contributes meaningfully to existing theoretical understanding while providing practical frameworks for personalized intervention strategies that extend beyond traditional one-size-fits-all approaches. Contemporary systematic reviews of artificial intelligence applications in personalized learning highlight the persistent challenge of translating sophisticated algorithmic capabilities into educationally meaningful interventions that respect individual learner differences and maintain pedagogical authenticity [36]. The achievement of 78.4% ± 2.1% early warning accuracy coupled with 79.8% ± 2.9% teacher satisfaction by such an unassuming framework indicates that closure may be reached with little compromise between the high-tech technological sophistication and educational utility that is found in many modern educational technology implementations. When viewed in light of the recent studies of the effects of POA on student psychological factors, it shows that student autonomy and intrinsic motivation can indeed be increased, rather than decreased, by well-designed forms of technology exposure [37].

The temporal learning trajectory analysis identifying different patterns of effectiveness across POA's three phases attests to the theoretical soundness of the approach, while providing empirical evidence in support of timely instructions strategies proposed in the literature that adds to existing systematic review evidence on the diversity of POA implementation and effectiveness across educational settings [38]. The framework's unique contribution over transformer-based multidimensional feedback systems is its theoretically informed stance on feature selection and interpretation, countering criticisms against recent AI-driven writing instruction tools on the possible hiatus between automated feedback generation and actual learning support [39]. Human expertise validation introduced at various stages of the algorithmic design makes certain that technological capabilities supplement, rather than supplant, professional pedagogical judgment and comes in light of the emerging evidence that the effective utilization of educational AI applications mandates a delicate balance between fully automated optimization and supervisory human control in order to sustain learning authenticity [40]. The framework's contribution extends beyond immediate performance improvements to establish methodological precedents for educational theory-informed machine learning that addresses fundamental challenges in learning analytics regarding the integration of sophisticated computational approaches with established pedagogical knowledge. The success of multi-theoretical integration within predictive modeling suggests promising directions for future educational technology development that prioritize theoretical coherence and practical utility over purely technical optimization metrics, thereby advancing the field toward more sustainable and educationally meaningful artificial intelligence applications in language instruction contexts.

5. Conclusion

The POA-MLSP model is an important step in the application of educational technology on language teaching, which successfully shows that the advanced machine learning techniques can be meaningfully combined with the traditional pedagogical theory for improving CET-4 writing performance prediction and assistance. Having produced an $R^2 = 0.75$ across five dimensions of writing and while receiving teacher satisfaction of 79.8% ± 2.9%, it demonstrates that developing educational technology solutions that reflect pedagogical authenticity can be balanced with technical expressiveness, and can resolve a potent dilemma in learning analytics: the linkage of algorithms to the practice of a classroom. The purposeful and principled incorporation of POA theory with SDT-based engagement modeling sets into motion a novel methodological precedent among literatures that seek to predict in educational contexts by fusing domain-specific knowledge and multi-theoretical models directly into algorithmic design. The discovery of five student engagement profiles and the 78.4% ± 2.1% prediction accuracy achieved in early warning detection show that the framework has the potential to provide personalized intervention strategies by bridging student autonomy and intrinsic motivation development. These findings imply potential research directions for future ed-tech development that is theoretically consistent and practical rather than focusing only on technical optimization criteria with limited educational significance. Framework scalability considerations include modular deployment options for institutions with varying technical capabilities, automated data collection mechanisms reducing manual teacher workload to sustainable levels, and cross-cultural adaptation protocols for implementation beyond Chinese university contexts. The minimal training requirements (4.8 hours initial setup, 25-30 minutes weekly operation) and cloud-based deployment options facilitate broader institutional adoption while maintaining educational effectiveness. The framework's contribution transcends immediate performance improvements to establish sustainable pathways for intelligent educational system development that respects the fundamental nature of teaching and learning processes while harnessing technological capabilities for enhanced educational outcomes. The validation of temporal learning trajectory patterns across POA's three phases provides empirical evidence for optimized instructional timing strategies that can inform broader curriculum design and implementation practices within English language education contexts. The successful deployment of the framework within authentic CET-4 writing instruction environments demonstrates the viability of theory-informed learning analytics for supporting data-driven pedagogical decision-making that enhances educational equity through personalized learning support while maintaining the essential human elements that characterize effective language instruction.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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