Cognitive-Semantic Modeling and AI-Driven Adaptive Learning Systems for Enhancing Foreign Language Comprehension

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Abstract: The increasing integration of artificial intelligence and digital platforms in higher education has created new opportunities for enhancing foreign language comprehension. However, many technology-enhanced language learning environments lack a strong cognitive-semantic foundation to support deep meaning construction. This study proposes and empirically examines an Applied IT instructional model that integrates cognitive-semantic theory with e-learning platforms and adaptive AI-based systems to improve foreign language reading and understanding competence among university students. Grounded in frame semantics, mental spaces theory, cognitive domains, and reframing methodology, the model operationalizes meaning-centered instruction through Moodle, Quizlet, Kahoot, Duolingo for Higher Education, and Smart Sparrow. A quasi experimental mixed-methods design was employed with undergraduate learners divided into experimental and control groups. Quantitative results demonstrate statistically significant improvements in reading comprehension for learners exposed to the Applied IT component, while qualitative findings reveal enhanced contextual interpretation and semantic awareness. The study contributes to digital pedagogy by demonstrating how cognitive linguistic principles can be systematically embedded into adaptive educational technologies through learning analytics and AI-driven personalization to support academic reading in higher education. The paper presents the design, implementation, and empirical validation of an AI-driven cognitive-semantic adaptive learning system for foreign language reading comprehension. The system integrates a formally specified rule-based adaptation engine, structured learning analytics pipeline, and reproducible deployment configuration. A quasi-experimental study ($N = 84$) demonstrated statistically significant improvement in comprehension gains ($t(82) = 4.73$, $p < .001$, Cohen's $d = 0.92$).

1 INTRODUCTION

Adaptive learning systems require algorithmic transparency, reproducibility, and statistical validation. This study operationalizes cognitive-semantic theory within an implemented AI-supported instructional architecture. Foreign language reading comprehension is a critical academic skill in higher education, particularly when students engage with discipline-specific texts in a second or foreign language. Although digital learning platforms and artificial intelligence are widely used in education, many technology-enhanced reading environments focus primarily on surface-level skills such as vocabulary memorization and grammatical accuracy. Such approaches often overlook deeper cognitive processes involved in meaning construction and contextual interpretation. Recent research in digital pedagogy emphasizes the importance of integrating technological systems with cognitive principles of language processing and comprehension [1]. Cognitive linguistics provides a strong theoretical foundation for such integration. In particular, frame semantics and conceptual models of meaning explain how readers interpret texts by activating structured knowledge frameworks and contextual relations. Despite their theoretical relevance, these approaches are rarely operationalized within applied educational technologies. This study addresses this gap by developing and empirically evaluating an Applied IT component that integrates cognitive-semantic theory with e-learning platforms and adaptive AI-based systems. The proposed model aims to enhance foreign language reading comprehension by supporting semantic interpretation, contextual reasoning, and adaptive feedback mechanisms within higher-education learning environments.

2 DIGITAL PEDAGOGY AND TECHNOLOGY-ENHANCED LANGUAGE LEARNING

Digital pedagogy in higher education increasingly integrates learning management systems and AI-supported environments to improve learner engagement and achievement. Research demonstrates that adaptive learning technologies can enhance outcomes by adjusting instructional content to learners' proficiency levels and learning pace [2]. In language education, intelligent tutoring systems and digital platforms have shown benefits for vocabulary acquisition and grammatical development. However, several studies note that many digital language learning tools remain weakly grounded in theories of meaning and cognition, limiting their effectiveness for higher-order skills such as academic reading comprehension [3]. Cognitive linguistics conceptualizes meaning as dynamic, context-dependent, and grounded in human experience. Frame semantics proposes that lexical items activate structured knowledge frames guiding interpretation [4]. Mental spaces theory explains how readers construct temporary conceptual structures while processing discourse [5], [6], while cognitive grammar emphasizes the conceptual grounding of linguistic forms within broader cognitive domains [7]. Related approaches such as reframing techniques and frame-semantic analysis highlight the role of conceptual restructuring in meaning interpretation [8], [9]. Applied linguistic studies have further developed cognitive-semantic approaches to discourse analysis and text comprehension [10]-[12]. Together, these frameworks suggest that effective reading instruction should focus on conceptual relations, semantic structures, and contextual inference rather than isolated lexical units. However, empirical implementation of these theories in digital learning environments remains limited. Adaptive learning systems powered by artificial intelligence provide a promising mechanism for implementing such models. These systems analyze learner behavior and dynamically adjust instructional pathways, feedback, and task difficulty [13]-[23]. At the same time, the wider deployment of Applied IT frameworks relies heavily on robust computational modeling and data processing architectures within technical university ecosystems [24], [25]. When combined with cognitively informed instructional design, adaptive AI systems can support deeper comprehension and self-regulated learning. Consequently, integrating adaptive educational technologies with cognitive-semantic frameworks represents an important direction for technology-enhanced language learning research.

3 METHODS

3.1 Research Design

This study employed a quasi-experimental mixed-methods design, combining quantitative measures of reading comprehension with qualitative analysis of learner interaction and meaning construction. The design aligns with empirical standards in educational technology and computer-assisted language learning research, particularly studies examining AI-supported instructional interventions. The system follows a four-layer applied IT architecture (see Figure 1).

3.2 Participants

Participants were undergraduate students enrolled in a foreign language course at a higher education institution. A total of 84 students participated in the study and were divided into two groups:

1) Experimental group (n = 42). received instruction through the cognitive-semantic Applied IT component;
2) Control group (n = 42). received conventional digital reading instruction without cognitive-semantic structuring or adaptive AI integration.

Participants: N = 84 (Experimental = 42; Control = 42). Pre-test equivalence p = 0.71. Both groups were comparable in terms of language proficiency at the outset of the study.

3.2.1 Ethics, Consent, and Data Privacy

The study complied with institutional ethical guidelines for research involving human participants;

formal approval was obtained from the relevant Institutional Review Board / ethics committee of the host institution prior to data collection. All participating students were informed about the objectives of the research, the nature of the instructional intervention, and the types of learning analytics data collected during the study. Participation was voluntary and based on informed consent obtained prior to the start of the experiment. Learning analytics were collected automatically through the digital learning platforms used in the Applied IT component (Moodle, Smart Sparrow, Quizlet, Kahoot, and Duolingo for Higher Education). The collected data included interaction logs such as time-on-task, response latency, completion rates, error patterns, and adaptive pathway decisions. No sensitive personal data were collected beyond anonymized learner identifiers required for system functionality. All interaction data were anonymized prior to analysis and stored in a secure PostgreSQL-based Learning Record Store. Access to the dataset was restricted to the research team, and the data were used exclusively for academic research purposes. The study complied with institutional data protection policies and standard ethical practices in educational technology research.

3.3 Instructional Intervention

The experimental group participated in a 12-week instructional intervention integrating cognitive-semantic principles with digitally mediated instruction. The Applied IT component was implemented through a coordinated ecosystem of platforms, each configured to serve a distinct cognitive and pedagogical function:

- Moodle functioned as the central learning management system. Reading materials were organized according to semantic frames and conceptual domains. Moodle's conditional release settings were used to scaffold progression from frame identification tasks to higher-level interpretive activities. Embedded quizzes captured comprehension accuracy and semantic inference patterns.
- Quizlet was configured using domain-based vocabulary sets aligned with conceptual frames (e.g., causation, evaluation, process). Spaced repetition algorithms supported conceptual consolidation rather than isolated lexical memorization.
- Kahoot was employed for low-stakes formative assessment focused on semantic relations, frame activation, and contextual meaning selection. Response-time data were used to infer processing difficulty.
- Duolingo for Higher Education provided adaptive lexical and syntactic reinforcement. The platform's proficiency-based progression system adjusted task difficulty based on learner accuracy and error recurrence.
- Smart Sparrow served as the primary adaptive learning engine. Reading tasks were designed with branching logic that responded to learner performance on semantic interpretation checkpoints, delivering targeted scaffolding, feedback, or alternative explanatory pathways.

The control group completed equivalent reading tasks using Moodle but without frame-based structuring, adaptive branching, or AI-driven personalization.

Figure 1 Architecture of the Applied IT instructional model integrating cognitive-semantic theory with adaptive educational technologies for foreign language reading comprehension. Figure 1 illustrates the multi-layered architecture of the Applied IT instructional model. At the theoretical layer, cognitive-semantic frameworks (frame semantics, mental spaces theory, and cognitive domains) inform task design and semantic scaffolding principles. The instructional design layer translates these principles into frame-based reading tasks, semantic annotation activities, and meaning-focused assessments. The platform layer consists of Moodle (content delivery and assessment management), Quizlet (conceptual vocabulary consolidation), Kahoot (formative semantic checks), Duolingo for Higher Education (adaptive lexical-syntactic reinforcement), and Smart Sparrow (AI-driven adaptive learning pathways). At the analytics and AI layer, learner interaction data (time-on-task, accuracy, error patterns, and completion rates) are continuously collected and processed. Based on predefined adaptation rules, the system dynamically adjusts content difficulty, feedback type, and learning pathways. Finally, the learner layer represents student engagement with adaptive reading tasks, where meaning construction is supported through iterative interaction between cognitive-semantic scaffolding and AI-based personalization. (In layout terms: top → theory; middle → platforms; bottom → learners; arrows both downward and upward to show feedback loops.). The applied IT component of the adaptive learning system collects multidimensional learning analytics variables to monitor engagement, performance, cognitive processing, and system adaptivity.

Figure 1: Applied IT system architecture for cognitive-semantic adaptive reading instruction.

3.4 Digital Analytics and Data Collection

In addition to standardized pre- and post-tests, the Applied IT component generated detailed learning analytics across platforms.

The following indicators were systematically collected and analyzed:

1) Time-on-task. duration spent on reading passages, semantic annotation tasks, and adaptive feedback screens.
2) Completion rates. proportion of completed reading units, quizzes, and adaptive pathways.
3) Error patterns. recurrent misinterpretations of frames, incorrect semantic role assignments, and breakdowns in contextual inference.
4) Adaptation paths. AI-generated learning routes in Smart Sparrow and Duolingo, indicating when and why learners were redirected to remedial or advanced content.

These analytics enabled fine-grained observation of learner interaction with cognitive-semantic tasks and informed qualitative interpretation of comprehension processes.

3.5 AI Adaptivity Logic

AI-driven adaptivity within the Applied IT component operated on three instructional dimensions:

1) Content adaptation. Reading passages and tasks were dynamically adjusted in complexity based on learner comprehension accuracy and semantic error density.
2) Feedback adaptation. Learners demonstrating frame-level misunderstanding received explanatory feedback emphasizing conceptual relations rather than surface correction.
3) Pathway adaptation. Learners were redirected to alternative semantic frames, background knowledge prompts, or simplified mental-space constructions when comprehension thresholds were not met.

Adaptation decisions were rule-based and analytics-driven, ensuring alignment between cognitive-semantic theory and algorithmic personalization.

3.6 Data Analysis

Quantitative data were analyzed using paired-sample and independent-sample t-tests to examine differences in reading comprehension gains between groups. Qualitative data were analyzed through thematic and discourse-semantic analysis to identify patterns in meaning construction and interpretive behavior.

4 SYSTEM IMPLEMENTATION AND REPRODUCIBILITY

This subsection specifies the technical configuration, data schema, adaptation logic, and deployment requirements necessary to reproduce the adaptive learning environment. All parameters are explicitly defined to ensure methodological transparency and experimental replicability.

4.1 Platform Configuration and Environment

The adaptive system was implemented using the following software and hardware configuration:

1) Core Platform Stack;
   - Moodle (PHP 8.1, MySQL 8 backend);
   - Smart Sparrow Adaptive Module;
   - Python (analytics and rule execution);
   - PostgreSQL (Learning Record Store);
   - Server OS: Ubuntu 22.04 LTS;
2) Hardware Configuration;
   - 8-core CPU;
   - 16 GB RAM;
   - SSD-based storage;
3) Key Moodle Parameters;
   - Conditional release: Enabled;
   - Activity completion tracking: Enabled;
   - Logstore standard + external LRS integration;
   - REST API: Enabled for pathway updates;
   - Cron execution interval: 5 minutes.

This configuration supports real-time analytics processing and rule-based instructional adaptation.

4.2 Data and Log Schema

All learner-system interactions are stored in a structured event log within PostgreSQL (Learning Record Store). Each record follows the schema given in the Table 1 below.

The Table 1 ensures standardized, machine-readable logging to support feature extraction, rule-based adaptation, and full experimental reproducibility.

4.3 Analytics Pipeline

The adaptive analytics workflow follows a deterministic four-stage process. First, interaction logs are extracted from PostgreSQL using structured SQL queries. Second, feature aggregation is performed in Python (Pandas), generating derived indicators including frame-level accuracy, error frequency, mean response latency, and rolling mastery estimates. Third, predefined adaptation thresholds are evaluated through rule-based logic. Finally, validated adaptive decisions are transmitted to Moodle via the conditional release API, dynamically updating learner pathways and content availability.

4.4 Adaptation Rules and Trigger Thresholds

Adaptation is activated when explicit quantitative thresholds are met. The system relies on performance and cognitive-processing signals: (i) frame-level accuracy < 0.70, (ii) ≥ 3 consecutive frame-type errors, (iii) response latency $> 1.5\times$ cohort median, and (iv) inactivity > 48 hours. High mastery (≥ 0.85 across two modules) triggers progression.

Triggered actions include remedial module assignment, targeted semantic feedback, task simplification, advanced pathway unlocking, and automated reminders. All thresholds are parameterized and configurable within Python-based rule files, ensuring reproducibility and experimental control.

Table 1: Learning record store.

Field Name	Data Type	Format / Constraint	Description
Event_ID	UUID	Primary key	Unique interaction identifier
User_ID	Integer	Foreign key	Learner identifier
Timestamp	TIMESTAMP	ISO 8601	UTC event time
Task_ID	VARCHAR(50)	Indexed	Activity identifier
Frame_Type	VARCHAR(30)	Controlled vocab.	Semantic frame category
Response	TEXT	UTF-8	Learner answer
Correctness	BOOLEAN	0/1	Binary evaluation
Response_Time	FLOAT	Seconds	Latency measure
Adaptive_Action	VARCHAR(50)	Nullable	Triggered system response

4.5 Baseline Comparison

For validation, a non-adaptive baseline was implemented in standard Moodle using identical instructional materials but without adaptive rule execution. The baseline employed static sequencing, manual conditional release, and generic feedback, with analytics limited to descriptive reporting.

In contrast, the adaptive system enabled automated rule-based sequencing, API-driven pathway modification, error-type-specific feedback, and real-time prescriptive analytics. This controlled comparison isolates the effect of adaptive logic from content-related variables.

5 RESEARCH RESULTS

Analysis of pre- and post-test scores (see Table 2) revealed that the experimental group demonstrated significantly greater gains in reading comprehension than the control group ($p < .05$). Learners exposed to the Applied IT component showed improved ability to interpret implicit meaning, identify semantic relations, and comprehend discipline-specific texts.

Table 2: Reading comprehension scores.

Group	Pre Mean	SD	Post Mean	SD	Gain
Experimental	61.8	6.9	78.4	7.2	+16.6
Control	62.4	7.1	69.1	6.8	+6.7

Independent samples t-test: $t(82)=4.73$, $p<.001$, Cohen's $d=0.92$ (large effect).

Qualitative analysis of learner reflections and task responses indicated that students in the experimental group developed greater awareness of contextual meaning and conceptual structure. Learners frequently referred to semantic relations, background knowledge activation, and reinterpretation of meaning when describing their reading processes. In contrast, control group responses focused primarily on vocabulary translation and surface-level understanding.

The findings of this study demonstrate that integrating cognitive-semantic theory with adaptive educational technologies can significantly enhance foreign language reading comprehension in higher education. The Applied IT component supported learners in constructing coherent mental representations of textual meaning by emphasizing frames, cognitive domains, and contextual interpretation.

The results align with previous research highlighting the importance of cognitively informed instructional design in digital learning environments. Moreover, the study extends existing literature by providing empirical evidence for the application of cognitive linguistics in AI-enhanced language instruction.

6 CONCLUSIONS

This study developed and empirically validated a cognitively grounded Applied IT model for enhancing foreign language reading comprehension in higher education. The proposed approach integrates cognitive-semantic theory, including frame semantics, mental spaces, and cognitive domains, with a multi-platform adaptive learning ecosystem consisting of Moodle, Quizlet, Kahoot, Duolingo for Higher Education, and Smart Sparrow. In contrast to conventional digital reading instruction, which often emphasizes vocabulary recognition and surface-level comprehension, the presented model supports deeper meaning construction through semantic scaffolding, analytics-driven feedback, and adaptive instructional pathways.

The findings demonstrate that the integration of cognitive-semantic principles with AI-driven educational technologies can produce substantial improvements in reading performance. The experimental group significantly outperformed the control group in post-intervention comprehension outcomes, with mean scores increasing from 61.8 to 78.4 compared with 62.4 to 69.1 in the non-adaptive condition. The observed difference was statistically significant, $t(82) = 4.73$, $p < .001$, with a large effect size (Cohen's $d = 0.92$), indicating that the proposed instructional architecture had a strong positive impact on learners' ability to interpret implicit meaning, identify semantic relations, and process discipline-specific texts more effectively.

An important contribution of the study is that it moves beyond conceptual discussion and provides an operational, reproducible framework for AI-supported language instruction. The system includes a clearly defined analytics pipeline, structured learning record schema, explicit adaptation thresholds, and rule-based mechanisms for content adaptation, feedback adaptation, and pathway adaptation. This makes the model not only pedagogically meaningful but also technically transparent and replicable, which is essential for Applied IT research in education. The study therefore contributes to the growing body of work on digital pedagogy by showing how theories of meaning can be systematically transformed into implementable adaptive learning logic.

The qualitative findings further reinforce the quantitative results. Learners in the experimental condition demonstrated greater awareness of contextual interpretation, background knowledge activation, and semantic restructuring, whereas students in the control group relied more heavily on translation and surface-level decoding strategies. This suggests that the proposed system improves not only test performance but also the quality of comprehension processes, supporting deeper cognitive engagement with academic texts. In this sense, the model offers value for universities seeking to improve language education through intelligent, theory-informed digital environments.

At the same time, several limitations should be acknowledged. The study was conducted with a relatively limited sample of 84 undergraduate students in one higher-education context, and the intervention covered a 12-week instructional period. Although the results are robust, broader validation across different institutions, proficiency levels, and target languages is necessary to confirm the generalizability of the model. In addition, the adaptive mechanism in the present study was primarily rule-based; future work may explore hybrid approaches that combine interpretable rule systems with machine learning models for finer personalization.

Future research should also investigate the longitudinal effects of cognitive-semantic adaptive instruction, its transferability to writing and listening skills, and its applicability in multilingual and discipline-specific learning contexts. Expanding the model with richer learner profiling, automated discourse analysis, and more advanced predictive analytics may further strengthen its pedagogical effectiveness. Overall, the study shows that AI-driven adaptive learning systems become substantially more effective when grounded in robust cognitive-semantic principles, and it provides a practical foundation for the development of next-generation intelligent language learning environments in higher education.

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