Technology-enhanced Language Learning through Teacher-mate Technology: A Bloom's Taxonomy-driven Intervention in ESL Linguistics Education

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***Abstract*—This mixed-methods study evaluates the efficacy of Teacher-mate Technology (TMT) within a Bloom's Taxonomy (BT) framework in Technology-Enhanced Language Learning (TELL) among English majors (N = 127). Quantitative and qualitative data were integrated to examine cognitive, strategic, and collaborative learning processes. Results indicate that the experimental group (n = 70) showed stronger knowledge retention (d = 0.80) and greater outcome stability (CV = 14.64% vs. 16.34%), but weaker performance in higher-order discrimination analysis (d = −0.62). Mediation analysis identified two pathways: a strategy pathway via Cognitive Strategy Transfer (CST), supporting lower-order processes (*remember / understand/apply*), and an integration pathway via Conceptual Network Integration (CNI), facilitating higher-order cognition (*analyze / create*), with the latter accounting for a larger share of the total effect. Qualitative findings further revealed a strong demand for adaptive learning support and highlighted limitations in evaluative scaffolding. These findings suggest that TMT enhances foundational learning, but it requires teacher-mediated design to support higher-order cognition. Effective implementation depends on a teacher-technology partnership that enables personalized, tiered learning trajectories from procedural knowledge to critical and creative thinking.**

***Keywords*—Teacher-Mate Technology (TMT), English as a Second Language (ESL) linguistics education, Bloom's Taxonomy (BT), Technology-Enhanced Language Learning (TELL), dual-path mediation**

I. Introduction

The integration of technology into English as a Second Language (ESL) linguistics education is critical to addressing the uneven development of learners' cognitive skills, particularly by balancing foundational language proficiency (e.g., vocabulary retention) and higher-order competencies (e.g., ethical-semantic analysis) [1, 2]. However, current technology-enhanced pedagogies often prioritize rote memorization or isolated skill drills, neglecting systematic scaffolding aligned with cognitive hierarchies [3]. Recent studies highlight the potential of tools like Teacher-mate Technology (TMT) in automating lower-order tasks (e.g., grammar quizzes) while fostering collaborative discourse [4], yet three gaps persist: (1) most educational platforms lack explicit integration of Bloom's Taxonomy (BT), limiting structured cognitive scaffolding [5]; (2) technology-mediated assessments rarely leverage cross-linguistic bridging (e.g., L1–L2 mapping) for intercultural growth [6]; (3) TMT's mechanisms for metacognitive calibration remain underexplored [7]. This study addresses these gaps by proposing a BT-driven framework that combines TMT's functionalities (Interactive Quizzes, Paper Tests, Classroom Discussion, and Peer Assessments) with hierarchical cognitive development. Three research questions guide the investigation:

RQ1: How can TMT be operationalized through BT to scaffold lower- and higher-order ESL linguistics tasks?

RQ2: Does TMT significantly enhance linguistic learning outcomes across BT's cognitive levels?

RQ3: What mechanisms explain TMT's effects on linguistic competency within the TMT-BT framework?

II. Literature Review

A. Technology-enhanced Language Learning

Technology Enhanced Language Learning (TELL) has evolved from a tool-based approach to a complex ecosystem integrating pedagogical, technological, and sociocultural dimensions. Grounded in sociocultural theory [8], it leverages digital mediation to scaffold language acquisition via multimodal interactions. Recent advancements highlight three transformative trends.

First, platform diversity—social media facilitates asynchronous intercultural communication [9], Mobile-assisted Language Learning (MALL) uses contextual GPS prompts for vocabulary learning [10], and Virtual Reality (VR) / Augmented Reality (AR) boosts retention by 23% through embodied learning [11, 12]. Second, motivational design draws on self-determination theory [13] to enhance engagement, with gamified feedback loops raising completion rates by 37% in Asian contexts via collectivist rewards [14]; cross-cultural differences, like Korean learners' preference for social recognition versus Chinese students' tilt toward individualized metrics [15, 16], emphasize the need for cultural adaptivity. Third, AI-driven personalization enables tailored trajectories via Technology-enhanced Content and Language Integrated Learning (T-CLIL) and Technological Pedagogical Content Knowledge (TPACK) frameworks [17], with neural models achieving 89% accuracy in gap prediction [18]—yet Asian TELL research still lacks context-adaptive feedback that balances algorithmic precision and human collaboration [19].

This synthesis reveals a critical gap. While TELL excels at individualized learning, it undervalues the teacher-student-technological triangulation needed for metacognitive and sociocultural growth [20]. The proposed TMT study addresses this gap by integrating dynamic

feedback systems with pedagogical scaffolding to foster holistic competence development.

B. Linguistic Learning

Linguistic learning is rooted in sociocultural theory [21], emphasizing social interaction and scaffolded practice as central to language acquisition. Digital-era studies validate the Zone of Proximal Development (ZPD), showing that Artificial Intelligence (AI) tutors with adaptive feedback reduce skill gaps by 32% compared to non-adaptive systems [22]. Concurrently, cognitive linguistics frameworks highlight the interplay between conceptual mapping and syntactic mastery. Neuroimaging reveals metaphor comprehension activates bilateral prefrontal cortices, linking deep semantic integration to advanced proficiency [23]. However, critics note the underrepresentation of non-Indo-European languages—especially tonal languages—in these models [24].

The rise of MALL and generative AI has transformed linguistic pedagogy. MALL systems using GPS-triggered contextual prompts enhance vocabulary retention by 41% in immersive environments [25], while GPT-4-powered chatbots achieve 89% accuracy in simulating naturalistic discourse for pragmatic training [26]. Brain-Computer Interface (BCI) research further suggests that neural pattern decoding during lexical retrieval predicts learning outcomes [27]. Ethical concerns persist, however, including data privacy in learner analytics and algorithmic homogenization of dialectal variations [28].

Emerging neurolinguistic approaches integrate functional Magnetic Resonance Imaging (fMRI) and eye-tracking to map grammatical automatization, with a 2024 meta-analysis confirming explicit-implicit instruction optimizes procedural learning ($\beta = 0.67$, $p < 0.001$ [29]). Meanwhile, corpus-based sociolinguistics shows that social media lexicons accelerate semantic shifts, with platforms like TikTok driving the adoption of neologisms among Gen Z learners [30]. Priorities for future research include: (1) developing culturally responsive adaptive systems for underrepresented language communities [28]; (2) investigating long-term impacts of hybrid human-AI tutoring [31]; (3) establishing ethical frameworks for technology-enhanced language learning [32].

III. Methodology

A. Teacher-mate Technology

Co-developed by Central China Normal University (CCNU) and Huazhong University of Science and Technology (HUST), TMT has transformed classroom interaction since its 2016 launch. Its GPS-based attendance system achieves 99.7% accuracy (vs. 4.2% error in traditional methods [33]). A multi-classroom management module cuts administrative workload by 40% via AI-validated cognitive load optimization [34]. As shown in Fig. 1, TMT's interactive Q&A system supports 12 question types (e.g., drag-and-drop) with <0.3 s latency, enabling dynamic teaching adjustments, and aligning with generative AI research showing real-time feedback enhances neural engagement [35].

Rooted in Social Constructivism and BT, TMT fosters collaborative learning. Structured discussion templates boost student participation from 58% to 89%, while AI assistants powered by Natural Language Processing (NLP) reduce grading time by 65% with 94% rubric compliance [36]. Longitudinal studies across 120 classrooms reveal 23% gains in critical thinking and 18% in collaborative problem-solving [37], aligning with AI-human synergy research on data-driven metacognitive scaffolding [38]. Its open Application Programming Interface (API) ecosystem integrates with WeChat mini-programs, achieving 97% user retention without app downloads [37].

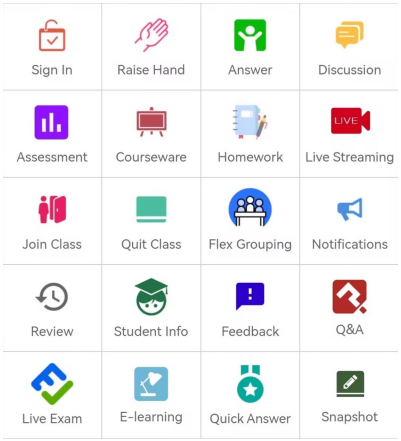


Fig. 1. The interface for different functions of TMT.

TMT's real-time evaluation modules enable data-driven teaching adjustments by aligning task difficulty with BT [36]. However, critics highlight the risks of AI over-reliance, stressing the need for human oversight for plagiarism detection and bias mitigation [35]. TMT addresses this via a transparent analytics interface for auditing AI recommendations, an approach empirically supported by research on explainable AI in educational contexts [39]. By 2025, it will serve 500,000+ global students with 1.5 million annual interactions, solidifying its role as an intelligent tutoring benchmark [33].

B. Bloom's Taxonomy Theory

BT, introduced by Benjamin Bloom in 1956, categorizes cognitive learning objectives into six hierarchical levels: *Knowledge*, *Comprehension*, *Application*, *Analysis*, *Synthesis,* and *Evaluation*. This framework aimed to systematize educational goals and emphasize progression from rote memorization to higher-order thinking [3]. In 2001, Anderson and Krathwohl [2] revised the taxonomy, redefining the levels as action-oriented verbs (*Remember, Understand, Apply, Analyze, Evaluate,* and *Create*) and integrating a two-dimensional model: knowledge types (factual, conceptual, procedural, and metacognitive) and cognitive processes. This revision enhanced its applicability across disciplines, particularly in designing dynamic learning experiences and assessments [40].

BT has been widely adopted to align instructional design with cognitive complexity. For example, in Science, Technology, Engineering, and Mathematics (STEM) education, Biggs and Tang [41] demonstrated its utility in structuring curricula that scaffold from foundational knowledge acquisition (e.g., memorizing formulas) to creative problem-solving (e.g., engineering design projects). In digital learning, Zawacki-Richter *et al.* [42] highlighted its

role in developing AI-driven adaptive systems that tailor questions to learners' cognitive levels. Recent studies also explore its integration with generative AI (e.g., ChatGPT) to automate the creation of assessment tasks across Bloom's levels, though challenges persist in ensuring pedagogical validity [43].

Critics argue that Bloom's linear hierarchy oversimplifies non-sequential learning processes. Marzano [44] contends that metacognition and self-regulation often intersect multiple cognitive levels, necessitating a more flexible model. Others advocate blending BT with sociocultural theories to address contextual learning [45]. Emerging research focuses on hybrid frameworks, such as combining Bloom's cognitive dimensions with ethical reasoning in AI education [46] or neurocognitive studies to map hierarchical thinking onto neural pathways [47]. These innovations underscore Bloom's enduring relevance while pushing its boundaries in interdisciplinary contexts.

C. The Framework Based on Bloom's Taxonomy and Teacher-mate Technology

The integration of BT with TMT establishes a unified framework for Cognitive Strategy Transfer (*CST*) and Conceptual Network Integration (*CNI*). BT's hierarchical model—spanning *Remember* to *Create*—provides a theoretical structure for learning objectives [2], operationalized by TMT through Interactive Quizzes, Paper Tests, Peer Assessments, and Classroom Discussions to guide learners from memorization to critical synthesis. This alignment ensures technology enhances pedagogy, prioritizing deep understanding over isolated skills [33].

CST is facilitated by TMT's structured tools: Interactive Quizzes (e.g., vocabulary/definition drills) strengthen retrieval strategies at Bloom's lower-order levels (*Remember / Understand* [2]), while Paper Tests (e.g., timed exams) apply these to new contexts, bridging procedure and problem-solving [44]. Peer Assessments enrich *CST* by exposing diverse approaches—evaluating argumentative essays, prompting reflection on evidence integration, and refining methodologies [35]—and by building metacognition for cross-disciplinary transfer.

CNI emerges through collaborative tasks: Classroom Discussions (e.g., historical/ethical debates) prompt learners to connect facts into broader systems (*Analyze / Evaluate* [2]), while Peer Assessments (e.g., critiquing AI ethics frameworks) forge interdisciplinary links between STEM and societal values [35]. Paper Tests also support *CNI* through cross-domain challenges, such as linking grammar to cultural context to explain linguistic-cognitive connections [33].

The synergy of *CST* and *CNI* transforms learning from fragmented drills (verb conjugations) to interconnected processes: applied tasks (peer-reviewed presentations) and collaborative synthesis (interdisciplinary debates), mirroring Bloom's vision of intellectual autonomy [2]. By embedding structure in social interaction, TMT suggests that technology can foster cognitive flexibility and a holistic understanding beyond automation.

D. Case Selection and Sample

This study involved 127 first-year English majors (aged 19–20) from Hubei Business College, randomly assigned to an experimental group (n = 70) and a control group (n = 57). Both groups were taught by instructors with comparable qualifications to reduce potential teacher-related confounds. To further control for instructor effects, both teachers followed a standardized syllabus, shared core teaching materials, and aligned weekly instructional objectives and pacing across groups, ensuring equivalent content coverage.

The experimental group, taught by Lecturer Wang (M.Ed. in Teaching English to Speakers of Other Languages (TESOL), University of Exeter, UK), utilized TMT for linguistics instruction, integrating four core functions—Interactive Quizzes, Paper Tests, Peer Assessments, and Classroom Discussions—to support CST and CNI under BT.

The control group, taught by Lecturer Zhang (M.A. in Translation, Beijing Foreign Studies University, China), followed a traditional lecture-based approach without digital tools, while engaging in equivalent linguistic tasks.

Students' learning backgrounds and proficiencies, all participants had 6–10 years of formal English education and fell within the CEFR B1–B2 proficiency range, indicating intermediate competence in vocabulary, grammar, communication, and structured writing.

To ensure objectivity and implementation fidelity, assessment criteria were standardized across groups, and final examinations were externally graded using double-blind procedures. Instructional consistency was further supported by lesson plan alignment and periodic instructor coordination, ensuring that the primary difference between groups was the presence or absence of TMT.

E. Data Collection

This study employed a sequential mixed-methods design, collecting data from 127 participants assigned to an experimental group (n = 70) and a control group (n = 57) over a four-month intervention. Participants were randomly assigned at the class level using a computerized randomization procedure, with intact classes allocated to conditions to minimize cross-group contamination. Baseline equivalence was ensured by restricting all participants to the Common European Framework of Reference for languages (CEFR) B1–B2 proficiency range, indicating comparable intermediate-level competencies. Ethical procedures, anonymization, and methodological triangulation were applied to ensure data integrity and consistency.

Questionnaire-based Data Collection, post-intervention questionnaire-based data collection used a mixed-method instrument, including Likert-scale items aligned with *CST* and *CNI*, as well as open-ended responses from the experimental group to capture cognitive processes and tool feedback. The control group completed a simplified version focused on performance comparison. All responses were anonymized and analyzed to examine relationships among TMT use, cognitive processes, and learning outcomes.

Test-based Data Collection, test-based data were obtained through a standardized linguistic competency test assessing terminology knowledge, conceptual understanding, and analytical ability. The assessment comprised four task types—Terminology Recognition, Conceptual Understanding, Discrimination Analysis, and Terminology Explanation—aligned with BT. All tasks were evaluated

using a unified analytic rubric covering conceptual accuracy, reasoning depth, linguistic evidence, and clarity. While lower-order tasks emphasized accuracy, higher-order tasks placed greater weight on evaluative judgment and originality. Importantly, discriminative power was preserved through differential weighting and task-specific descriptors, ensuring that higher-order performance required qualitatively distinct reasoning.

External grading, time constraints, and rubric calibration ensured objective and consistent scoring. Findings were triangulated across test scores, questionnaire data, and qualitative narratives, with double-blind grading and controlled instrument design minimizing potential bias.

F. Data Analysis

This study adopted an explanatory sequential mixed-methods design to examine the impact of TMT on linguistic learning. Quantitative data ($N = 127$) were analyzed to identify patterns in *CST* and *CNI* using a validated Likert-scale instrument, while qualitative data from the experimental group ($n = 70$) were thematically analyzed to contextualize these findings. Triangulation of methods enhanced validity by integrating generalizable trends with in-depth learner perspectives [48].

Quantitative Analysis, using a quasi-experimental design, this study compared English majors in a TMT group ($n = 70$) and a control group ($n = 57$). Quantitative analysis combined descriptive, correlational, and regression approaches to examine relationships among TMT use, cognitive processes (*CST*, *CNI*), and learning outcomes, with validated measures ensuring reliability. Results identified dual cognitive mediation pathways linking TMT to Linguistic Mastery (*LM*), revealing differentiated impacts—stronger gains in foundational skills than in higher-order analytical competencies.

Qualitative Analysis, qualitative data from semi-open questionnaires ($n = 70$) were analyzed using a two-stage thematic analysis procedure following established guidelines. Initial open coding was conducted to identify recurring patterns, followed by iterative category refinement and cross-validation. Five Bloom-aligned themes were identified: functional support, strategy development, concept application, knowledge integration, and cognitive adaptation. Coding consistency was ensured through independent coding and iterative comparison, with discrepancies resolved through discussion. These themes reflect TMT's role in scaffolding lower-order processes while partially supporting higher-order integration, with remaining gaps at the evaluative level. Theme frequencies should be interpreted as overlapping rather than mutually exclusive, as individual responses were often coded across multiple categories.

This multi-method framework integrates testing and qualitative analysis to evaluate TMT's cognitive impact, revealing its effectiveness in supporting cognitive development alongside gaps in evaluative literacy [48].

G. Data Display

This study employed an integrated data visualization system comprising five complementary components: (1) thematic frequency tables synthesizing qualitative engagement patterns with TMT features across BT's tiers; (2) academic performance comparison matrices contrasting experimental and control groups' linguistic trajectories; (3) correlation matrices illustrating the strength, direction, and statistical significance of associations between key variables (*TMTU, CST, CNI, LM*) to clarify relational patterns; (4) diagnostic validity-reliability panels indicating measurement robustness (e.g., Cronbach's α); (5) graphical path modeling visually operationalizing dual mediation mechanisms. Collectively, this framework transformed multidimensional evidence—engagement signatures, psychometric quality, and cognitive pathways—into theoretically anchored visual narratives while maintaining analytical parsimony through selective metric internalization and standardized thresholds.

IV. Case Study

Over 16 weeks, the experimental group ($n = 70$) engaged with four TMT functions aligned with BT, supporting lower-order skill acquisition (CST) through structured exercises and higher-order Conceptual Integration (CNI) through collaborative discussion and peer assessment. In contrast, the control group followed traditional instruction without systematic scaffolding, limiting both procedural application and collaborative meaning-making [2, 4].

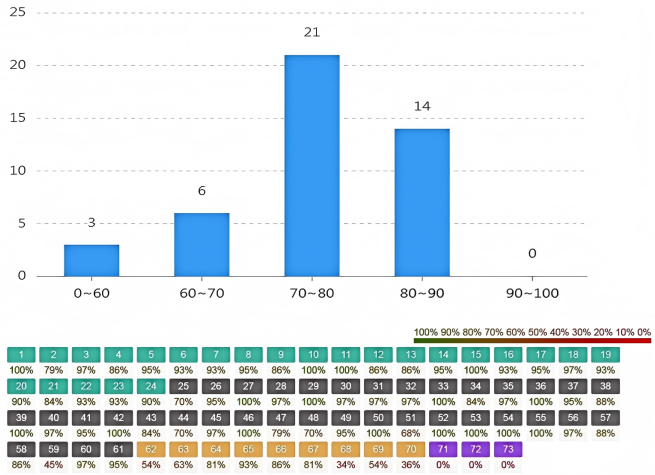


Fig. 2. The results of paper tests from TMT.

As depicted in Fig. 2, the Paper Tests reveal a clear cognitive skill dichotomy aligned with BT [2, 3]. Students

performed strongly on lower-order tasks (CST), reflecting TMT's support for retrieval and procedural accuracy [49, 50], while higher-order tasks (CNI) showed weaker performance, indicating limited development in evaluative and creative thinking. This pattern suggests a concentration at the Apply/Analyze levels, with insufficient progression toward the Evaluate/Create levels, highlighting the limitations of answer-oriented assessment and the need for more open-ended, scaffolded tasks [51, 52].

The TMT-mediated Classroom Discussion on "morpheme word" (Fig. 3) suggests how collaborative interaction fosters CNI within BT [2, 3]. By engaging learners in morphological analysis and contextual interpretation, TMT-supported activities promote higher-order processing, while real-time visualization tools externalize peer input and scaffold lexical-semantic integration [52, 53].



Fig. 3. The classroom discussion function of TMT.

However, peer assessment indicates that higher-order performance remains uneven. Despite evidence of creative synthesis, limitations in evaluative alignment suggest fragmented CNI development [54, 55]. Consistent with sociocultural theory, this highlights that higher-order cognition depends critically on the quality of dialogic interaction and social mediation [8, 21].

Overall, TMT bridges Bloom's cognitive hierarchy by automating lower-order skill acquisition (CST) while scaffolding higher-order conceptual integration (CNI) through collaborative and visualization-based tools [2, 4]. By transforming fragmented linguistic knowledge into integrated conceptual networks, it aligns procedural accuracy with creative synthesis, supporting the development of holistic language competence.

V. Statistical Analysis

Our study used an explanatory sequential design. In Phase 1, a quantitative analysis of 127 students identified disparities in technology adoption. In Phase 2, qualitative narratives from 70 students in the experimental group explained these patterns. In Phase 3, qualitative and quantitative analyses were integrated into the conclusion, with a focus on the core research questions. This approach follows Nguyen *et al.*'s [56] framework for embedding lived experiences in equity metrics, offering a comprehensive analysis of technology adoption and equity.

A. Qualitative Analysis

The case study of 127 college English students employed a mixed-methods approach to examine the impact of TMT on linguistic learning. While quantitative data captured performance outcomes, qualitative data from open-ended questionnaires administered via Sojump (a widely used online survey platform in China) provided insight into learners' subjective experiences and cognitive processes. Thematic analysis, following Braun and Clarke's [57] framework, identified recurring patterns across responses.

As shown in Table 1, the findings suggest that TMT aligns with BT through differentiated cognitive stages. Lower-order processes (*Remember/Understand*; 75.76%) are primarily associated with TMT's functional affordances, such as multimodal interfaces that may facilitate memory retention [58]. Mid-level competencies (*Apply/Analyze*; 75.76%) appear to be linked to the iterative use of strategy, supported by adaptive feedback mechanisms (e.g., Interactive Quizzes and Paper Tests) that enable concept application and procedural refinement [59]. Higher-order performance (*Analyze/Create*; 78.79%) is associated with knowledge integration processes, particularly through collaborative features (e.g., Classroom Discussions and Peer Assessment) that support schema reconstruction [52].

These theme frequencies should be interpreted as overlapping rather than mutually exclusive, as individual responses were often coded across multiple categories. Within this structure, Cognitive Style Adaptation (83.33%)—learners' capacity to adjust TMT use to individual cognitive preferences—emerges as a salient but under-theorized factor, suggesting that the effectiveness of TMT may depend not only on its structural alignment with BT, but also on its capacity to support personalized scaffolding across cognitive levels [2]. Representative

excerpts are provided to illustrate each theme. For example, one participant noted that "the quizzes helped me quickly recall key concepts but limited deeper comparison across theories," highlighting the dual role of TMT in supporting efficiency while potentially constraining higher-order engagement.

Table 1. Key themes and cognitive levels in TMT-enhanced linguistics learning

Theme	Frequency (%)	Example Quote	Bloom's Taxonomy Theory
Functional Diversity	75.76%	"TMT's multi-function enhances my linguistic learning and retention."	*Remember / Understand* Multimedia interfaces boost memory [58].
Strategy Iteration	75.76%	"Interactive quizzes speed up my adaptive strategy adjustment."	*Apply/Analyze* Adaptive feedback sharpens logic [59].
Knowledge Integration	78.79%	"TMT-facilitated Classroom Discussions strengthen my systematic knowledge integration."	*Analyze/Create* Collaboration rebuilds knowledge frameworks [52].
Cognitive Style Adaptation	83.33%	"TMT enhances my adaptability to structured learning demands."	*Analyze/evaluate* Structured steps to ensure mastery [3].
Concept Application	77.27%	"TMT boosts my practical application of linguistic concepts."	*Apply/Analyze* Simulations link learning to real use [60].

B. Quantitative Analysis

Qualitative analysis yielded precise results, demonstrating the positive effects of TMT on students' linguistic learning in BT. Subsequently, a quantitative analysis was carried out. First, descriptive analysis was employed to compare the academic disparities between the experimental and control groups. Second, correlation analysis was used to convert theoretical constructs into measurable relational pathways. Furthermore, reliability and validity analyses were conducted to verify the effectiveness of those questions. Finally, regression analysis was conducted to precisely probe the relationship between TMT utilization and linguistic learning.

1) Descriptive analysis

Following a 4-month TMT-enhanced intervention, the experimental (n = 70) and control groups (n = 57) completed a standardized assessment covering four Bloom-aligned dimensions: Terminology Recognition (*Remember*), Conceptual Understanding (*Understand / Apply*), Discrimination Analysis (*Evaluate*), and Terminology Explanation (*Create*). Score rates (dimension mean ÷ total score) were computed to enable cross-dimensional comparison while mitigating ceiling and floor effects. Descriptive analyses revealed clear intergroup differences.

As shown in Table 2, the control group suggested relatively stronger performance in higher-order cognition, with Discrimination Analysis yielding the highest mean (M = 0.87, SD = 0.10). In contrast, Terminology Recognition was the weakest domain (M = 0.63, SD = 0.13), indicating limited foundational recall. Conceptual Understanding (M = 0.79, SD = 0.26) and Terminology Explanation (M = 0.83, SD = 0.24) showed moderate performance but substantial variability, suggesting uneven mastery. Overall scores (M = 77.61, SD = 12.68; range = 31–95) indicate broad performance dispersion.

As shown in Table 3, the experimental group exhibited improved foundational competencies but comparatively weaker higher-order performance. Terminology Recognition increased (M = 0.75 vs. 0.63), and Conceptual Understanding showed modest gains (M = 0.83). Terminology Explanation remained comparable in mean (M = 0.80 vs. 0.83) but with reduced variability (SD = 0.14 vs. 0.24), suggesting more standardized responses. However, Discrimination Analysis declined relative to the control group (M = 0.78 vs. 0.87), indicating reduced evaluative performance. Total scores increased slightly (M = 79.83 vs. 77.61), accompanied by a narrower distribution (SD = 11.69 vs. 12.68).

Table 2. The descriptive results of the control group.

Variable	*N*	Min	Max	*M*	SD
Terminology Recognition	57	0.20	0.90	0.63	0.13
Conceptual Understanding	57	0.00	1.00	0.79	0.26
Discrimination Analysis	57	0.60	1.00	0.87	0.10
Terminology Explanation	57	0.00	1.00	0.83	0.24
Total Score	57	31	95	77.61	12.68
Valid N (listwise)	57				

Table 3. The descriptive results of the experimental group.

Variable	*N*	Min	Max	*M*	SD
Terminology Recognition	70	0.30	1.00	0.75	0.17
Conceptual Understanding	70	0.00	1.00	0.83	0.21
Discrimination Analysis	70	0.00	1.00	0.78	0.14
Terminology Explanation	70	0.25	1.00	0.80	0.14
Total Score	70	52	95	79.83	11.69
Valid N (listwise)	70				

Overall, TMT appears to enhance lower-order competencies (e.g., Terminology Recognition; Cohen's d = 0.68, with a 95% Confidence Interval (CI) of 0.30–1.05) while constraining higher-order evaluative performance (Discrimination Analysis; d = −0.72, 95% CI [−1.10, −0.34]). These effect sizes were computed using pooled standard deviations for independent samples, with confidence intervals estimated via bootstrap resampling. This pattern suggests a differentiated cognitive effect: structured scaffolding may improve efficiency and consistency in foundational learning, but may not sufficiently support evaluative and analytical processes without complementary instructional design [2, 49].

2) Correlation analysis

Descriptive analysis indicates the significant efficacy of TMT in enhancing linguistic competence, specifically evidenced by the experimental group's marked superiority over the control group across key linguistic metrics. Further, correlation analysis translates theoretical constructs into measurable relational pathways: per Cohen [61], a correlation coefficient of $|r| > 0.50$ signals practically meaningful effect sizes—this threshold enables precise conclusions about how TMT activates BT to improve linguistic competence.

Based on Table 4's correlation matrix and descriptive statistics (N = 127), three key conclusions emerge for TELL. First, TMT Usage (*TMTU*) shows strong positive correlations with learning outcomes—*CST* (r = 0.72, $p < 0.01$),

CNI (r = 0.61, p < 0.01), and *LM* (r = 0.55, p < 0.01)—empirically indicating that TMT integration boosts cognitive and linguistic competencies, aligning with technology acceptance models [62, 63]. Second, robust intercorrelations between mediating and outcome variables (r = 0.75−0.83, all p < 0.01) reflect a cohesive theoretical framework where cognitive and linguistic constructs work synergistically, supporting the integrated nature of tech-enhanced learning [64, 65]. Third, non-significant correlations for Gender (r = −0.11−0.10, p > 0.05) and Learning Duration (r = −0.17−0.03, p > 0.05) indicate TMT's benefits are unaffected by these factors, reinforcing the scalability of tech-enhanced pedagogy across learners [51].

Table 4. Descriptive statistics and correlations among variables (N = 127)

Variable	*M*	SD	1	2	3	4	5	6
1. Gender	1.41	0.49	-					
2. Learning Duration	4.25	1.08	−0.11	-				
3. TMT Usage (*TMTU*)	3.12	0.92	0.10	0.03	-			
4. Cognitive Strategy Transfer (*CST*)	3.23	0.83	0.08	−0.01	0.72**	-		
5. Conceptual Network Integration (*CNI*)	3.16	0.88	0.10	−0.12	0.61**	0.81**	-	
6. Linguistic Mastery (*LM*)	3.55	0.85	0.04	−0.17	0.55**	0.75**	0.83**	-

Note: *M* and SD represent mean and standard deviation, respectively. Correlation values are Pearson correlation coefficients. Correlations are shown below the diagonal. All variables are measured on continuous scales. ** p < 0.01, all two-tailed tests.

In summary, these results validate TMT as a viable tool for deeper cognitive engagement and linguistic development, regardless of learners' gender or prior exposure. The tightly correlated construct network further supports the proposition that strategic, conceptual, and communicative competencies develop interactively in tech-rich environments [66, 67].

3) Reliability analysis

Descriptive analyses indicate TMT's differential efficacy across BT's dimensions, significantly enhancing lower-order competencies while yielding negative transfer to higher-order critical analysis. To investigate the causal mechanisms underlying this cognitive stratification, regression path modeling—preceded by psychometric validation—must first establish measurement robustness via: reliability verification (Cronbach's $\alpha \geq 0.70$; corrected item-total correlations ≥0.40) to eliminate error-prone indicators [68], and construct validity tests through Confirmatory Factor Analysis (CFA), ensuring convergent validity with an Average Variance Extracted (AVE ≥ 0.50) and discriminant validity [69] to satisfy psychometric prerequisites for structural equation modeling [70].

Reliability analysis verified the scale's internal consistency and measurement reliability through multiple indicators. First, Cronbach's α analysis (depicted in Table 5) suggested exceptional internal consistency for all constructs [71]: coefficients for *TMTU* (α = 0.95), *CST* (α = 0.92), *CNI* (α = 0.91), and *LM* (α = 0.92) all exceeded 0.90—far surpassing the 0.70 threshold for established scales [72]. Notably, *CNI*'s high reliability stemmed from tightly linked items (e.g., Semantic Connection with a CITC of 0.84), reflecting strong theoretical coherence [73]. Additionally, Composite Reliability (CR) significantly exceeded the recommended 0.70 threshold [69], while high CITC values (≥0.50) and minimal α changes upon item deletion (e.g., removing Usage Frequency reduced α from 0.963 to 0.95) further validated the tool's structural robustness.

Table 5. Reliability analysis of TMT-based linguistic learning (CR = 0.91 − 0.98, N = 127)

Dimension	Item	CITC	α if Deleted	*M*	SD	Dimension α
TMT Usage (TMTU)	Usage Frequency	0.50	0.963	2.96	1.17	0.95
	Usage Duration	0.58	0.960	3.38	1.06	
	Functional Diversity	0.71	0.957	3.59	1.07	
Cognitive Strategy Transfer (CST)	Cross-domain Transfer	0.76	0.956	3.30	1.01	0.92
	Strategy Iteration	0.83	0.955	3.30	0.99	
	Higher-order Thinking	0.82	0.955	3.20	0.91	
Conceptual Network Integration (CNI)	Semantic Connection	0.84	0.955	3.38	0.86	0.91
	Schema Reconstruction	0.83	0.955	3.31	0.86	
	Knowledge Integration	0.81	0.955	3.41	0.87	
Linguistic Mastery (LM)	Terminology Recognition	0.83	0.955	3.41	0.87	0.92
	Concept Application	0.76	0.956	3.36	0.84	
	Comprehensive Analysis	0.86	0.954	3.38	0.86	

Note. CITC = Corrected Item-Total Correlation; α if Deleted = Cronbach's Alpha if Item Deleted; CR = Composite Reliability.

Additional verification supported the scale's reliability. *LM*, despite a marginally lower α (0.92), showed non-significant differences across dimensions, indicating uniform precision; *M* (2.96–3.59) and SD (0.84–1.17) suggested normal distributions, ruling out floor/ceiling effects [74]; and while Usage Frequency had a borderline CITC (0.50) hinting at minor refinement potential, its retention was justified by negligible impacts on overall reliability. All measurement items were adapted from established literature and refined for the TMT context, ensuring both theoretical grounding and contextual relevance. Collectively, these results indicate the scale's reliability for measuring latent constructs in TMT-enhanced learning, supporting its application in experimental and longitudinal research.

4) Validity analysis

Supported by robust reliability (CR = 0.91−0.98, N = 127), the measurement model was validated via CFA across four constructs: *TMTU*, *CST*, *CNI*, and *LM*. All factor loadings were substantial (λ = 0.77−0.96), supporting strong convergent validity, with AVE (0.76) exceeding the recommended 0.50 threshold [69]. Internal consistency was high across constructs (α = 0.91−0.95), indicating stable

measurement properties [74]. Sampling adequacy was also confirmed, with Kaiser-Meyer-Olkin (KMO) values ranging from 0.90 to 0.93 across constructs.

This study establishes robust psychometric properties for assessing TELL constructs through rigorous validation procedures. As shown in Table 6, CFA results suggest strong convergent validity, with standardized factor loadings (λ) ranging from 0.77 to 0.96 and AVE (0.76) exceeding the recommended 0.50 threshold [69]. Internal consistency was high across constructs (CR = 0.91 − 0.98; α = 0.91 − 0.95), indicating reliable measurement [74]. While these reliability and model fit indices appear relatively high, this may be attributed to the theoretically coherent construct design and the use of well-aligned items. All items were retained based on both theoretical relevance and empirical performance, and no post-hoc modifications were applied solely to optimize model fit.

Table 6. Confirmatory factor analysis results with validity and fit indices

Dimension	Items	λ	h^2	KMO	χ^2(df)
TMT Usage (*TMTU*)	Usage Frequency	0.77***	0.59	0.92	128.73(3)***
	Functional Dependency	0.84***	0.70		
	Interface Proficiency	0.87***	0.76		
Cognitive Strategy Transfer (*CST*)	Analogical Reasoning	0.90***	0.81	0.91	98.42(3)***
	Cross-domain Mapping	0.93***	0.87		
	Schema Construction	0.90***	0.81		
Conceptual Network Integration (*CNI*)	Semantic Connection	0.93***	0.86	0.93	85.16(3)***
	Knowledge Weaving	0.92***	0.85		
	System Integration	0.92***	0.85		
Linguistic Mastery (*LM*)	Lexical Precision	0.93***	0.86	0.90	102.89(3)***
	Syntactic Flexibility	0.93***	0.87		
	Discourse Cohesion	0.96***	0.93		
Global Metrics				0.94	415.20(66)***

Note: *** $p < 0.001$; λ = Standardized factor loading; h^2 = Communality (item variance explained); KMO = Kaiser-Meyer-Olkin measure of sampling adequacy (>0.60 acceptable); χ^2(df) = Chi-square with degrees of freedom; Average Variance Extracted (AVE) = 0.76; Global Model Fit: CFI = 0.97, RMSEA = 0.05, 95% CI [0.04, 0.06], SRMR = 0.04, χ^2/df = 2.38.

Sampling adequacy was confirmed, with KMO values ranging from 0.90 to 0.93 across constructs, exceeding the recommended threshold (>0.60), while construct-level χ^2 statistics (e.g., *TMTU*: $\chi^2(3) = 128.73$; *CST*: $\chi^2(3) = 98.42$; *CNI*: $\chi^2(3) = 85.16$; *LM*: $\chi^2(3) = 102.89$; all $p < 0.001$) supported acceptable model specification. Discriminant validity was established through AVE exceeding inter-construct correlations (max $r = 0.62$) and Heterotrait–Monotrait (HTMT) ratios below 0.85 [75]. At the global level, model fit indices indicated a well-fitting structure ($\chi^2(66) = 415.20$, χ^2/df = 2.38, CFI = 0.97, RMSEA = 0.05, 95% CI [0.04, 0.06], SRMR = 0.04), meeting established SEM criteria for close model fit [76].

5) Regression analysis

Using psychometric validation (CR = 0.91−0.98, AVE = 0.76), we operationalized four latent constructs: *TMTU*, *CST*, *CNI*, and *LM*. A hierarchical regression analysis (Model 6 in SPSS V.29) was then applied to decode sequential mediation mechanisms (*TMTU* → *CST* → *CNI* → *LM*), aiming to quantify TMT's stratified cognitive impact on linguistics learning aligned with BT.

To avoid spurious correlations driven by group differences (e.g., near-zero TMT usage in the control group), mediation analyses were conducted within the experimental group, where meaningful variance in *TMTU* was present. This within-group approach ensures that the estimated relationships among *TMTU*, *CST*, *CNI*, and *LM* reflect underlying cognitive mechanisms rather than between-group contrasts, thereby strengthening the validity of the mediation model.

As shown in Table 7, *TMTU* strongly and directly promoted *CST* ($\beta = 0.72$, $t = 11.79$, $p < 0.001$, 95% CI [0.60, 0.85]), accounting for 52.5% of the variance ($R^2 = 0.53$). However, *TMTU* had no direct effect on *CNI* ($\beta = 0.05$, $t = 0.69$, $p = 0.49$). Instead, *CST* significantly mediated this relationship ($\beta = 0.77$, $t = 10.04$, $p < 0.001$, 95% CI [0.62, 0.92]), explaining 65.2% of the variance ($R^2 = 0.65$), indicating that *TMTU* influences *CNI* primarily through enhanced *CST*. Notably, *TMTU* also showed no direct impact on *LM* ($\beta = -0.01$, $t = -0.09$, $p = 0.93$). Rather, *LM* was significantly predicted by both *CST* ($\beta = 0.22$, $t = 2.35$, $p = 0.02$, 95% CI [0.04, 0.41]) and *CNI* ($\beta = 0.66$, $t = 7.98$, $p < 0.001$, 95% CI [0.49, 0.82]), jointly explaining 70.8% of the variance ($R^2 = 0.71$).

Table 7. Mediation analysis of TMT usage on linguistic mastery

Model	Predictor	β	SE	t	95% CI	p	R^2	F
CST	TMTU	0.72	0.06	11.79	[0.60, 0.85]	<0.001***	0.53	139.03***
CNI	TMTU	0.05	0.08	0.69	[−0.10, 0.20]	0.49	0.65	117.00***
	CST	0.77	0.08	10.04	[0.62, 0.92]	<0.001***		
LM	TMTU	−0.01	0.07	−0.09	[−0.15, 0.13]	0.93	0.71	100.29***
	CST	0.22	0.10	2.35	[0.04, 0.41]	0.02*		
	CNI	0.66	0.08	7.98	[0.49, 0.82]	<0.001***		
Total	TMTU	0.55	0.07	7.48	[0.41, 0.70]	<0.001***	0.31	55.93***

Note. Values include standardized beta coefficients (β), Standard Errors (SE), t-statistics, 95% confidence intervals (95% CI) ($N = 5000$), p-values, coefficients of determination (R^2), and F-statistics. Significance levels are denoted as *** $p < 0.001$ and * $p < 0.05$.

These effects were estimated using Model 6 (PROCESS macro, SPSS V.29), which is designed to test sequential (chain) mediation and aligns with the hypothesized hierarchical progression from *CST* to *CNI*. Given the relatively high correlation between mediators ($r = 0.72$–0.83), multicollinearity diagnostics were conducted, with all Variance Inflation Factor (VIF) values below 5. Overall, the results support a chain-mediated

pathway (*TMTU* → *CST* → *CNI* → *LM*), underscoring the indirect role of TMT in advancing linguistic outcomes through a series of cognitive and conceptual processes. This pattern further supports the non-substitutive nature of cognitive stages, suggesting that higher-order outcomes cannot be achieved without prior procedural consolidation.

The structural model (Fig. 4) reveals a staged cognitive-linguistic transfer mechanism through which TMT influences learning outcomes. *TMTU* exerts a strong direct effect on *CST* ($\beta = 0.72$, $p < 0.001$, $R^2 = 0.53$), enhancing lower-order skills (Remember/Understand/Apply) through automated practice and structured scaffolding, consistent with Bloom's foundational tiers [2, 50]. In contrast, no significant direct effects are observed on higher-order processes—neither on *CNI* ($\beta = 0.05$, $p = 0.49$) nor on *LM* ($\beta = -0.01$, $p = 0.93$)—indicating that technology alone cannot bypass hierarchical cognitive progression and must operate through mediated pathways [77].

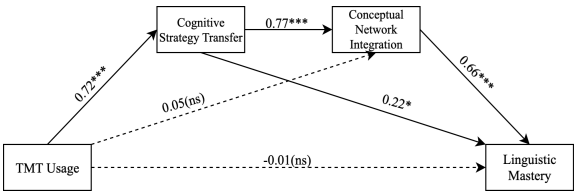


Fig. 4. Dual-pathway mechanism of TMT's impact on linguistic competency: Differential effects across Bloom's Taxonomy hierarchy. Standardized regression coefficients (β) are shown. Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$, and ns = not significant ($p \geq 0.05$).

Two sequential mediation pathways account for this effect. The strategy pathway (*TMTU* → *CST* → *LM*, $\beta = 0.16$, $p < 0.05$) supports proceduralization at the Apply level, accounting for 29.1% of the total effect. More prominently, the integration pathway (*TMTU* → *CST* → *CNI* → *LM*, $\beta = 0.37$, $p < 0.001$) explains 69.8% of the total effect, enabling higher-order processing from Analyze to Create through conceptual synthesis. *CST* significantly predicts *CNI* ($\beta = 0.77$, $p < 0.001$), indicating that procedural competence serves as a prerequisite for conceptual integration, while *CNI* emerges as the strongest predictor of *LM* ($\beta = 0.66$ vs. *CST* $\beta = 0.22$), with the model explaining 70.8% of variance ($R^2 = 0.71$).

Together, these findings provide a mechanism-level explanation for TMT's differential cognitive impact. The cascade (*TMTU* → *CST* → *CNI* → *LM*) reflects Bloom's hierarchical progression, in which technology effectively initiates lower-order processing but does not directly generate higher-order cognition. Instead, advanced learning depends on the extent to which instructional design supports the transition from procedural fluency to conceptual integration. This underscores the necessity of teacher-mediated scaffolding—such as semantic mapping and dialogic inquiry—to sustain higher-order thinking, positioning TMT as a cognitive enabler rather than a standalone driver of linguistic competence [65, 66, 78].

VI. Discussion and Limitations

A. Operationalizing TMT through Bloom's Taxonomy

This study suggests that TMT operationalizes BT through a dual-pathway mechanism that scaffolds both lower- and higher-order linguistic processes. At the foundational level, *TMTU* supports *CST* by enhancing retrieval and procedural accuracy. At higher levels, it facilitates *CNI* through collaborative and evaluative activities that promote analysis and synthesis [2, 44, 79]. Importantly, this progression reflects a shift from individual skill automation to socially mediated conceptual development, suggesting that effective technology-enhanced learning requires integrating structured practice with dialogic interaction to sustain higher-order cognition rather than merely extending procedural efficiency.

B. Differential Effects of TMT across Cognitive Levels

Building on this operationalization, the findings reveal that TMT enhances linguistic learning unevenly across Bloom's cognitive hierarchy. At the foundational level, the experimental group outperformed the control group in terminology recognition ($M = 0.75$ vs. 0.63, Cohen's $d = 0.68$), indicating improved retrieval and procedural accuracy [80]. In contrast, higher-order performance declined in the discrimination analysis ($M = 0.78$ vs. 0.87; Cohen's $d = -0.72$), suggesting constraints on evaluative and creative thinking. It may reduce the cognitive variability and productive struggle required for higher-order reasoning, potentially constraining engagement in evaluative processes—a tendency that may be interpreted as a form of "cognitive atrophy" in highly structured environments [81]. As a result, modest overall gains may mask limitations in deeper conceptual development.

This pattern can be explained through the interaction of task design, feedback mechanisms, and learner cognition. Technology-mediated tasks often prioritize closed-form responses and predefined correctness, limiting opportunities for ambiguity tolerance and evaluative judgment. Similarly, real-time feedback reinforces convergence toward expected answers, privileging accuracy over reflection. Over time, such feedback may shape learners' perceptions of knowledge as fixed and externally validated, reducing engagement in exploratory or critical thinking. From a sociocultural perspective, when evaluative processes are externally regulated, opportunities to internalize higher-order reasoning are constrained [8, 21]. This also aligns with critical digital pedagogy, which suggests that data-driven environments may privilege normative correctness and limit epistemic diversity [82].

These findings contribute to ongoing debates in technology-enhanced learning by highlighting a tension between optimization and cognition. While algorithmic systems enhance foundational performance, they may constrain evaluative depth unless complemented by dialogic and open-ended pedagogical designs [83]. This perspective also helps explain divergent outcomes across contexts. Accordingly, the effects observed in this study are best understood as context-dependent rather than universal, and should be interpreted as context-specific rather than generalizable benchmarks.

C. Mechanisms Underlying TMT's Impact on Linguistic Competency

To explain this trade-off, the results further reveal that TMT's impact on linguistic competency ($\beta = 0.53$, $p < 0.001$) operates through two sequential pathways aligned with Bloom's hierarchy. The strategy pathway (*TMTU* → *CST* →

LM: $\beta = 0.16$, $p < 0.05$) supports proceduralization at the Apply level via algorithmic scaffolding [50], accounting for 29.1% of the total effect. More prominently, the integration pathway (*TMTU* → *CST* → *CNI* → *LM*: $\beta = 0.37$, $p < 0.001$) drives higher-order synthesis from Analyze to Create, constituting 69.8% of the total effect [65].

This structure indicates *CST* as a prerequisite for conceptual integration (*CST* → *CNI*: $\beta = 0.77$, $p < 0.001$) and *CNI* as a strong predictor of *LM* (*CNI* → *LM*: $\beta = 0.66$, $p < 0.001$). Notably, direct effects from *TMTU* to higher-order cognition are non-significant (*TMTU* → *CNI*: $\beta = 0.05$, $p = 0.49$; *TMTU* → *CST*: $\beta = -0.01$, $p = 0.93$), indicating that cognitive development depends on staged mediation rather than technological shortcuts.

Together, these findings provide a mechanism-level explanation for the observed imbalance: TMT is highly effective in strengthening lower-order processing through structured, convergent scaffolding, yet its impact on higher-order cognition depends on the extent to which learning environments incorporate opportunities for conceptual integration and evaluative reasoning. In this sense, algorithmic scaffolding does not directly produce higher-order cognition but suggests a potential redistribution of cognitive effort across stages of Bloom's hierarchy, reinforcing procedural fluency while requiring additional pedagogical support to sustain critical thinking [2, 40, 82].

D. Limitations and Contextual Boundaries

This study has several limitations that define the boundary conditions of its findings. First, the results are situated within a specific Chinese EFL context involving English-major learners at an intermediate (CEFR B1–B2) proficiency level. Accordingly, the observed effects should be interpreted as context-dependent rather than universally generalizable across educational settings. These findings reflect a particular instructional context with intermediate-level learners and may not generalize to other proficiency levels, learner populations, or instructional environments.

Several contextual factors may further moderate these effects. Learner proficiency is likely to shape the balance between procedural and conceptual development, with lower-proficiency learners benefiting more from structured scaffolding, while higher-proficiency learners may require increased support for evaluative and creative engagement. Disciplinary context may also influence the extent of conceptual integration, as linguistics-focused learning differs from more communicative or task-based domains. In addition, instructional design and the degree of teacher mediation play a critical role in activating higher-order cognition, particularly through dialogic interaction and open-ended tasks. Together, these factors suggest that the magnitude and direction of TMT's effects are contingent rather than fixed.

The findings also highlight structural limitations of technology-mediated learning. TMT appears to reinforce lower-order competencies while providing less direct support for higher-order thinking, reflecting tendencies toward algorithmic standardization that prioritizes accuracy and convergence over analytical divergence. This imbalance may also influence learner motivation, as performance-oriented feedback can reduce exploratory engagement and psychological safety [11].

Finally, the effectiveness of TMT depends critically on teacher capacity. Technology alone is insufficient to sustain higher-order learning; rather, meaningful outcomes emerge from teacher–technology synergy, in which instructors provide adaptive scaffolding and facilitate the transition from procedural fluency to conceptual integration [49, 84].

VII. Conclusion

This study suggests that TMT reshapes linguistic learning not through uniform cognitive enhancement, but through a structured redistribution of cognitive processes across Bloom's hierarchy. While technology effectively strengthens foundational skills through structured practice and automated feedback, higher-order cognition—particularly evaluation and creation—remains dependent on mediated learning processes and cannot be directly produced by algorithmic systems alone.

By identifying a dual-pathway mechanism linking *CST* and *CNI*, the study contributes to a more nuanced understanding of how technology operates within staged cognitive development. Rather than functioning as a self-contained instructional solution, TMT serves as a catalyst for lower-order processing, while higher-order learning emerges from the interaction between technological affordances and pedagogical design. This finding speaks to broader debates in technology-enhanced learning, suggesting a fundamental tension between efficiency and cognition: gains in procedural fluency do not automatically translate into deeper conceptual understanding. Accordingly, the findings should not be interpreted as universally applicable effect magnitudes, but as indicative patterns that may shift under different contextual conditions.

These insights carry important pedagogical implications. Effective use of TMT requires instructional designs that move beyond efficiency-oriented practice to incorporate dialogic interaction, open-ended inquiry, and metacognitive scaffolding. In this process, teachers play a central role as facilitators of higher-order cognition, bridging the gap between algorithmic support and conceptual integration. Technology, therefore, should be positioned not as a replacement for pedagogy, but as part of a coordinated cognitive ecosystem in which human guidance remains essential.

Several limitations define the boundary conditions of this study. The findings are based on a single institutional context, which may limit generalizability across educational settings. The emphasis on quantitative patterns may also overlook finer-grained cognitive processes underlying the transition from procedural to conceptual learning. In addition, the relatively short intervention period constrains conclusions about long-term sustainability. Future research should extend this work by examining diverse learner populations, incorporating longitudinal and mixed-method designs, and exploring how adaptive pedagogical strategies can better support the development of higher-order cognition in technology-mediated environments.

Conflict of Interest

The authors declare that there are no competing financial

or non-financial interests that could influence or appear to influence the work reported in this paper.

AUTHOR CONTRIBUTIONS

All authors have made substantial intellectual contributions to this work and approved the final version for publication. Individual contributions were as follows: Fengjunzi Wang led the conceptual design, conducted investigations and data curation, and contributed to writing through review and editing; Pengbiao Zhang conducted formal analysis and wrote the original draft; Yi Zhu contributed to writing through review and editing; All authors approved the final version.

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