Exploiting Teacher-Mate Technology for College English Vocabulary Augmentation: A Cognitive-Constructivist Empirical Research

Pengbiao Zhang and Fengjunzi Wang*

Department of Foreign Languages, Hubei Business College, Hubei, China
Email: Joshua.zhangpb@gmail.com (P.Z.); wangfengjunzi@hbc.edu.cn (F.W.)
*Corresponding author

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***Abstract*—In the domain of Technology-Enhanced Language Learning (TELL), this research, grounded in Cognitive-Constructivist principles, explores the efficacy of Teacher-Mate Technology (TMT) in promoting English vocabulary acquisition among 144 non-English major students. Quantitative analysis using Statistical Product and Service Solutions (SPSS) V.29 on test scores and engagement data revealed substantial improvements in vocabulary retention and application. In contrast, qualitative analysis via Sojump indicated that 78.38% of learners reported enhanced vocabulary acquisition. TMT significantly enhanced vocabulary-dependent skills like writing and translation but had a restricted impact on overall language performance, particularly in reading comprehension. The results validate TMT's alignment with the Constructivist tenets of active learning, social interaction, and personalized knowledge construction. However, the study also highlights the need for supplementary strategies to foster holistic language development, thus offering educators a theoretically grounded, technology-enhanced approach to vocabulary instruction and contributing to the growing body of knowledge in TELL.**

***Keywords*—Teacher-Mate Technology (TMT), vocabulary acquisition, cognitive-constructivist pedagogy, Technology-Enhanced Language Learning (TELL)**

I. Introduction

The integration of Technology-Enhanced Language Learning (TELL) in Chinese universities faces a critical challenge: while digital tools like Quizlet show pedagogical promise [1], 72% of undergraduates still lack Common European Framework of Reference for Languages (CEFR) B1 vocabulary competence [2]. This discrepancy highlights two research gaps in China's technology-driven "New Liberal Arts" reform. First, most studies focus on generic platforms rather than specialized systems with real-time feedback. Second, few implementations apply Cognitive-constructivist principles to vocabulary acquisition through collaborative technology [3].

This study examines how Teacher-mate Technology (TMT) addresses these gaps through two lenses: (1) the practical effectiveness of its collaborative features in lexical development, and (2) the theoretical alignment between automated feedback systems and constructivist learning models. Building on Chapelle's [4] technology-mediated assessment framework, our investigation advances TELL application design and vocabulary acquisition theory in Chinese EFL contexts. The main research questions are:

Q1: What is the rationale behind the TMT-enhanced vocabulary learning process through the perspective of Cognitive-constructivist?

Q2: What is the association between the utilization of the TMT and students' English vocabulary learning outcomes?

Q3: Does TMT have a similarly obvious positive impact on students' vocabulary memory and comprehensive academic performance?

II. Literature Review

A. Technology-Enhanced Language Learning

Contemporary TELL frameworks have evolved through three developmental strands. Technological mediation theory posits that digital tools scaffold language acquisition through multimodal interaction [5]. This encompasses social media platforms [6], mobile-assisted learning systems [7], and immersive technologies like Virtual reality (VR) / Augmented Reality (AR) [8], which collectively enhance environmental authenticity and cognitive engagement [9].

Motivational design studies demonstrate TELL's capacity to stimulate learner autonomy through progress tracking and gamified mechanics [10, 11]. Particularly in Asian contexts, meta-analytic evidence confirms gamification's superior efficacy over traditional pedagogies in sustaining motivation [12, 13]. Personalization paradigms highlight adaptive systems' role in delivering customized learning trajectories. Recent implementations integrating T-CLIL methodologies with TPACK frameworks [14] exemplify how intelligent tutoring systems balance technological affordances with constructivist principles.

This tripartite progression underscores TELL's transition from tool-centric applications to theoretically grounded pedagogical ecosystems. The synthesis reveals critical Asian-specific evidence gaps regarding context-adaptive feedback mechanisms and collaborative learning architectures-lacunae central to our TMT investigation.

B. Vocabulary Acquisition

Vocabulary acquisition, as the cornerstone of language competence [15], necessitates strategic memory encoding mechanisms. Cognitive psychology frameworks elucidate three fundamental retention pathways.

Structural consolidation through spaced repetition systems (SRS), operationalizing Ebbinghaus' forgetting curve via algorithm-driven tools like Anki [16]. Associative reinforcement combines mnemonic devices [17] with dual coding theory [18], where lexical items are anchored through multimodal representations (visual-verbal associations in Memrise). Contextual integration merges task-based learning [19] with authentic language environments, enabling form-meaning-function triangulation [20].

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Emerging TELL applications synthesize these principles through gamified architectures (Duolingo's skill trees) and adaptive learning analytics [21]. However, Nemati [22] cautions against universal application, particularly for learners with cognitive differences requiring customized strategy training. Current research gaps persist in balancing algorithmic efficiency with pedagogical flexibility, a critical consideration for developing context-sensitive vocabulary learning systems.

C. Cognitive-Constructivist Framework for TMT

Interactive quizzes, the function of interactive quizzes of TMT is in line with Piaget's theory. Learners can expand their understanding of known concepts. For example, with the word "book", they can build on its noun meaning and, via the quiz's immediate feedback, learn its verb form. This process of assimilation (incorporating new info) and accommodation (adjusting mental frameworks) is key to Piaget's view of learning [23]. TMT's quizzes offer a practical way for learners to experience these cognitive processes in language learning.

The immediate feedback from TMT's interactive quizzes significantly aids vocabulary retention. Research by Cepeda *et al*. on spaced repetition and mnemonic techniques shows its importance. When learners get instant quiz feedback, they better remember word forms and meanings. This feedback corrects misconceptions quickly, leading to improved long-term retention. Therefore, TMT's interactive quizzes are a valuable tool for vocabulary learning.

Classroom discussions, TMT's classroom discussions follow Vygotsky's [24] sociocultural theory. Learners analyze concepts from different angles during peer interactions, like exploring the semantic and cultural sides of idioms. This matches Vygotsky's Zone of Proximal Development (ZPD), where interaction with more knowledgeable peers boosts cognitive growth and understanding. Honebein [25] said multiple-perspective experiences are key in constructivist learning, which TMT's discussions provide. Driscoll [26] emphasized social-based learning, a feature of TMT. Therefore, TMT's discussions help with social knowledge building.

TMT-supported collaborative learning is important for cognitive development. Tam [27] noted collaborative learning's role in instructional design, relevant to TMT. Honebein stressed student ownership in learning, which TMT's features support. Driscoll said students need time to build relationships, which TMT's discussions and activities can offer. Overall, TMT's collaborative learning aspects enhance the learning process.

Student Data Analytics, TMT's student data analytics offer personalized scaffolding. Learners can modify their learning strategies using performance metrics. This is in line with Driscoll's ideas on tailoring instruction to individual needs. Siemon *et al*. [28] stress data analytics' role in giving personalized feedback, a key TMT design feature. Liu *et al.* [29] highlight using data analytics to spot student needs and offer targeted help, which TMT can do. Sharma [30] discusses technology for personalized learning, enabled by TMT's interactive features and data analytics.

Personalized scaffolding via data analytics helps learners find areas to improve and adjust strategies, leading to better learning outcomes. Siemon *et al*. [31] emphasize using data analytics to boost learning outcomes through targeted support. Liu *et al*. [32] talk about data analytics enhancing student engagement, which can improve outcomes. Sharma also notes technology-enhanced personalized learning's potential to improve student performance.

III. Materials and Methods

A. The Introduction to Teacher-mate Technology

Teacher-Mate Technology (TMT), an advanced classroom interaction technology, emerged from the collaborative endeavors of the School of Psychology at Central China Normal University and the technical team of Huazhong University of Science and Technology. Since its initial introduction in 2016, it has attained a remarkable level of market penetration. It has been well-received by over 10,000 teachers and approximately 500,000 students and has spurred more than 1.5 million effective classroom interactions [33].

As shown in Fig. 1, Teacher-mate Technology, a classroom interaction tool for teachers, transforms teaching in multiple aspects. For classroom management, its online attendance and one-click sign-in, using real-time positioning, record attendance accurately. The multi-classroom management helps teachers organize different classes and share information smoothly, ensuring resource allocation.

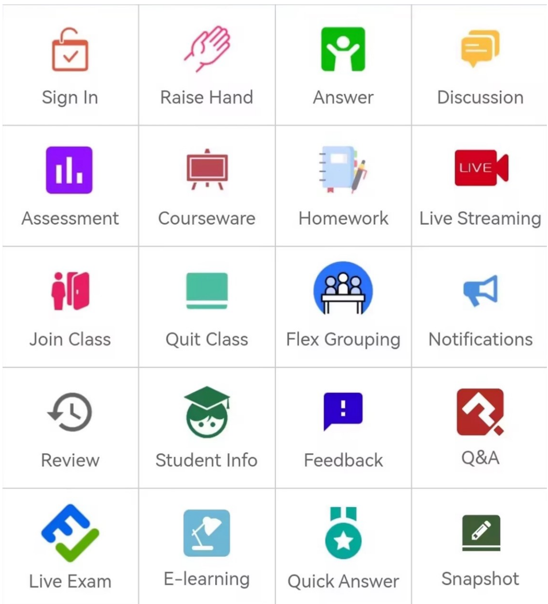

Fig. 1. The interface for different functions of TMT.

In teaching implementation, interactive answering, with various question types and real-time feedback, enables teachers to control the pace. Classroom discussion, following the teaching rhythm, encourages students to exchange ideas and explore knowledge deeply.

Regarding teaching support and technology integration, teaching assistants can be invited for detailed guidance, and the process evaluation tracks students' performance. The open integration allows connection with other tools, and the WeChat platform enables convenient interaction without app downloads, enhancing teaching quality and efficiency.

B. The Theory of Cognitive-Constructivist

Cognitive-Constructivist Theory emerges from Piaget's developmental epistemology and Vygotsky's sociocultural theory, positing knowledge as dynamic constructions shaped through learner-environment interactions. Glasersfeld's [34] radical constructivism redefined this paradigm, emphasizing learners' active meaning-making processes. These foundations were pedagogically operationalized through instructional models prioritizing schema evolution and socially mediated learning [35], establishing a framework where cognition develops through continuous adaptation.

The theory's dual cognitive processes drive knowledge construction: assimilation integrates new information into existing schemata (e.g., expanding "book" from noun to verb concepts), while accommodation restructures mental frameworks to resolve conceptual conflicts [36]. These mechanisms manifest through three evidence-based approaches: (a) situated cognition in authentic contexts [37], (b) cognitive apprenticeship through guided participation [38], and (c) metacognitive scaffolding for self-regulated learning [39].

Current research navigates critical tensions between constructivist flexibility and curricular standardization [40] while exploring intelligent tutoring systems' capacity to personalize learning within learners' zones of proximal development. This technological integration creates new synergies between cognitive theory and TELL innovations, particularly in adaptive systems like TMT that computationally operationalize constructivist principles, a transformative nexus informing our investigation of vocabulary acquisition mechanisms.

C. Cognitive-Constructivist Theory and TMT's Role in Vocabulary Memory

Cognitive-constructivist theory emphasizes that learners actively build knowledge through interactions. TMT's features effectively support this process, enhancing vocabulary memory. Quizzes prompt students to use existing knowledge to answer questions. For example, understanding "professional" in different contexts (noun vs. adjective) helps them integrate new meanings. Immediate feedback encourages active thinking, aiding in constructing word meanings rather than passively receiving information [41]. Discussions allow students to share diverse views, enriching their understanding. For instance, analyzing "idioms" from multiple angles deepens knowledge.

Exploring words from semantic, pragmatic, and cultural aspects builds a comprehensive vocabulary system. Data analytics offer insights into students' progress, enabling tailored strategies. Teachers can adjust teaching, and students can focus on weak areas. Feedback helps students refine their approaches, ensuring effective vocabulary building [42]. Quizzes, discussions, and data analytics create an environment where students actively construct vocabulary knowledge. Social interaction and personalized feedback enhance memory and understanding, aligning with Cognitive-Constructivist principles.

In short, TMT's tools promote active, social, and personalized learning, boosting vocabulary memory in line with Cognitive-Constructivist theory.

D. Case Selection and Sample

In this study, 144 first-year non-English-major college students aged 17-18 (60 males and 84 females) were selected. The sample was divided into two experimental groups and two control groups.

Experimental Groups, Experimental Group 1: comprising 32 students, it was taught by Lecturer Wang, who holds a Master of Education in TESOL from the University of Exeter (UK) and has the lecturer title. TMT was used for English teaching. Experimental Group 2: with 40 students, also taught by Lecturer Wang. It was set up to account for special class situations like significant academic differences among students. TMT was implemented for English instruction.

Control Groups, Control Group 1 consisting of 32 students, was taught by Lecturer Zhang, who has a Master of Arts in foreign languages from the University of California, Berkeley (US) and is a lecturer. Traditional teaching methods were applied. Control Group 2 comprising 40 students, was taught by Lecturer Huang, who holds a Master of Art in Educational Leadership from Manchester Metropolitan University (UK) and is a lecturer. Similar to Control Group 1, traditional teaching was used.

All instructors have overseas study backgrounds and the lecturer title, which helps minimize teacher-related confounding factors. To ensure objective evaluation and reduce bias, student performance assessment in all groups was standardized. All instructors used the same criteria for evaluating assignments and participation, and external teachers graded the final exam papers. This setup allows for a clear comparison between TMT-based teaching in the experimental groups and traditional teaching in the control groups.

Students' Learning Backgrounds and Proficiencies, the students in this study had a learning background of 6-10 years of mostly traditional classroom-based English learning. Their English examination scores, especially in the Chinese college entrance examination test (scoring 40-100 out of 150), placed them at CSE L1-L3 and CEFR A1-B1 levels, indicating a relatively weak English foundation. This makes them an ideal sample for observing the effects of different teaching methods on students with such a basis.

In terms of proficiency, their vocabulary ranged from 2,000-3,500. They were more competent in simple sentences and common tenses in grammar. However, complex clauses posed challenges. In speaking, they could manage simple daily conversations, but pronunciation and fluency needed enhancement. In writing, they could handle basic tasks like daily letters, posters, and dialogues, yet faced issues with format norms and language variety.

E. Data Collection

Data for this research have been obtained from four distinct data collection approaches: platform-based data collection, questionnaire-based data collection, test-based data collection, and interview-based data collection. Data were gathered over 4 months of one semester in 2024. Each data collection method was directed by an individual set of guidelines to ensure that both ethical and methodological requirements were fulfilled.

Platform-based data collection, learning records from TMT will be retrieved for the experimental groups consisting of 72 students through platform-based data collection. These records encompass the frequency of question-answering, participation in discussions, the accuracy ratio of answered questions, individual scores in quick-response tests, and individual comprehensive evaluations. Such data will serve as the basis for analyzing learning processes, learning interests, and learning outcomes within the experimental context.

Questionnaire-based data collection, during the mid-term and end-of-term periods, questionnaires will be distributed through platforms such as TMT and Sojump. The primary aim of these questionnaires is to investigate the affective attitudes of the experimental group students towards English learning, their utilization of learning strategies, and their evaluations and experiences regarding the TMT-enhanced learning process. This will provide valuable insights into the students' subjective experiences and perspectives within the learning environment enhanced by TMT.

Test-based data collection, English application-ability test questions, formulated according to the 9-level classification of the Chinese Language Proficiency Scale, will be administered to all 144 students. This will determine their CSE application-ability levels, which are then mapped to the CEFR level range. This mid-term assessment offers a semester-based snapshot of students' language proficiency.

All 144 students from four classes will take a standardized college English exam. It covers basic language knowledge and skills, including vocabulary retention, vocabulary application, vocabulary adaptation, reading comprehension, sentence translation, and short-essay writing. The data obtained will quantitatively measure students' semester-end learning achievements, facilitating a comprehensive assessment of their language-learning progress.

Students from the experimental group will be randomly chosen for in-depth interviews. These interviews will explore their experiences, challenges, and the impact of TMT on language learning. Key topics include teaching-method transformations due to technology and TMT's influence on students' vocabulary-learning feedback. This qualitative method complements quantitative data, providing a more comprehensive understanding of the learning process in the experimental context.

F. Data Analysis

In this study, an explanatory sequential mixed-methods design [43] was used to analyze different types of data. Quantitative data was first analyzed using Statistical Product and Service Solutions (SPSS) V.29, providing initial insights. Then, qualitative exploration was conducted, such as interviewing low-scoring TMT users, to gain a deeper understanding. Sojump was used to collect qualitative data through online questionnaires and interviews, enriching data sources. This approach combined the strengths of quantitative and qualitative data, enhancing the reliability and validity of the research findings.

Quantitative analysis, quantitative analysis in this research comprehensively explores the relationship between TMT application and student performance. 144 college students are divided into four groups, and their exam results after a semester are statistically analyzed by SPSS to examine the causal link between TMT and academic performance. Survey-based research is also used to enrich data. For test and platform data, a two-step analysis is adopted: first, the TMT platform's functions for preliminary exploration, and then SPSS V.29 for in-depth analysis of metrics like means, standard deviations, and association, which helps assess TMT's impact on performance.

Qualitative analysis, in this research, qualitative data collected via Sojump from questionnaires and interviews were analyzed. Coding and thematic analysis were used to extract key themes and viewpoints from these data sources. This approach helped to understand students' experiences and changes, uncovering subjective aspects not revealed by quantitative data. The focus of the qualitative analysis was on exploring students' experiences and changes during the learning process. In the case study of 72 college English students, this qualitative analysis was crucial for evaluating the impact of TMT on performance. By complementing quantitative analysis, it provided a more comprehensive understanding of the educational context, bringing to light hidden subjective and attitudinal details.

G. Data Display

Data presentation involves multiple aspects. For quantitative data, student exam scores are tabulated with group and test-component details for comparison. Bar graphs show average scores per test for different groups, along with descriptive statistics like means, standard deviations, and ranges. Factor and regression analyses explore the TMT-vocabulary learning relationship. For qualitative data, key themes and frequencies are presented in thematic tables, along with relevant interview quotes. To provide a comprehensive view, quantitative and qualitative data are presented side-by-side for specific aspects, and their discussion is integrated into the text.

IV. Result and Discussion

This chapter presents empirical findings from a semester-long case study examining the integration of Teacher-mate Technology (TMT) within an experimental cohort. Guided by Constructivist principles, post-intervention questionnaires were administered to evaluate learners' perceptions of TMT's pedagogical functions. Quantitative data from standardized final examinations (N=144) were analyzed using SPSS V.29 to systematically investigate correlations between TMT implementation and the development of lexical competence alongside comprehensive English proficiency. The triangulated methodology aligns with rigorous mixed-methods research paradigms, ensuring both theoretical grounding and empirical validity in assessing technology-mediated language acquisition outcomes.

A. Case Study

During the semester, the experimental groups mainly used the Interactive Quizzes, Classroom Discussion, and Student Data Analytics functions of TMT, which are in line with Constructivist principles. The Interactive Quizzes promoted active learning by engaging students in immediate problem-solving, while the Classroom Discussion function fostered social interactivity and collaborative learning. The Student Data Analytics function allowed for self-assessment and tracking of learning progress, enabling personalized learning experiences. In contrast, the control groups were taught using traditional methods without these TMT functions, which did not emphasize the active, social, and contextual aspects of learning as much.

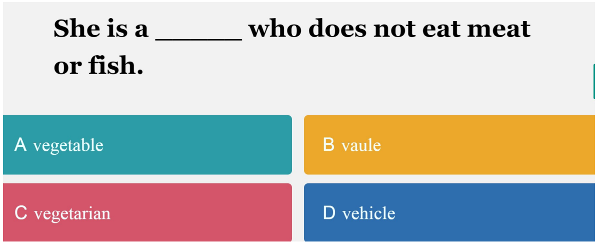

Fig. 2. The interactive quizzes of TMT.

As depicted in Fig. 2, in the Interactive Quizzes function of TMT, experimental group students receive immediate vocabulary questions during class. For instance, they might be asked to fill in the blank in the sentence "She is a ____ who does not eat meat or fish." with options like "vegetable," "value," "vegetarian," and "vehicle." The correct answer is "vegetarian," which tests their understanding of word meaning and context. This type of question helps students to actively think about the precise meaning of words and avoid semantic confusion, aligning with the Cognitive -Constructivist approach. Hmelo-Silver emphasizes the importance of active learning and problem-solving in Constructivism. Research by Bhandari *et al*. [44] also shows that interactive methods enhance learning efficiency and outcomes. Piaget's theory of constructivism further supports the effectiveness of this approach, highlighting the importance of active knowledge construction through direct experience and social interaction.

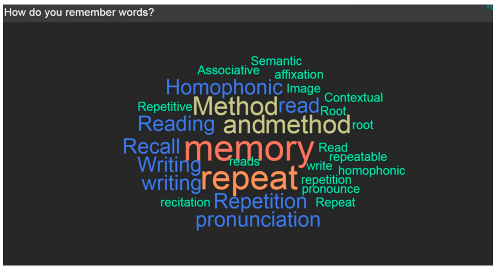

Fig. 3. The classroom discussion function of TMT.

In the experimental group using TMT, the classroom discussion function was vital for promoting social interactivity and collaborative learning, key elements of Constructivism. For instance, as depicted in Fig. 3, in a discussion about "How do you remember words?", students shared various methods like memory, repetition, reading, and writing. This interaction lets students learn from each other and form their understanding of effective vocabulary learning. The word cloud from the discussion showed diverse ideas, reflecting active knowledge construction through social interaction. This matches Constructivist theory, which sees learning as social and interactive. Hmelo-Silver stresses the role of social interaction in knowledge building. TMT's discussion function lets students have meaningful talks and exchange ideas. Bernard *et al*. [45] also found that interactive learning environments boost learning outcomes and deepen understanding.

In the experimental group's TMT case study, the Student Data Analytics function offered valuable insights into the classroom performance-final grade relationship, as seen in Fig. 4. The scatter plot shows a strong positive correlation (r = 0.7). This indicates that students more engaged in classroom activities, like discussion participation, interactive quiz completion, and learning material engagement, were likely to get higher final grades.

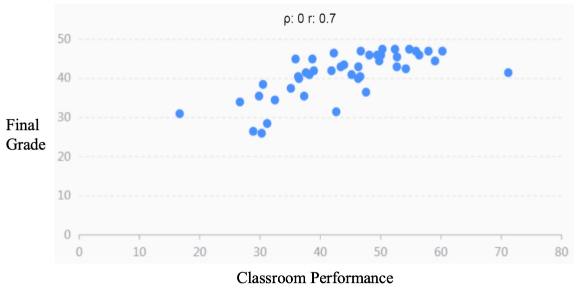

Fig. 4. The student data analytics of TMT.

This finding aligns with Constructivist theory, emphasizing that active learning participation leads to better outcomes. The TMT-enabled data-tracking helped educators identify students needing extra support and adjust teaching strategies. Research by Bernard *et al*. backs the effectiveness of interactive, data-informed teaching. Hmelo-Silver also stresses technology's role in promoting active learning, consistent with the TMT-enhanced learning environment's results.

B. *Statistical Analysis*

Our study used an explanatory sequential design. In Phase 1, a regression analysis of 144 students quantified technology adoption disparities. In Phase 2, qualitative narratives from marginalized groups explained these patterns. This approach follows Nguyen *et al*.'s [46] framework of using sequential mixed methods to embed lived experiences in equity metrics, offering a comprehensive analysis of technology adoption and equity.

Qualitative Analysis, The case study of 72 college English students employed a mixed-methods approach to evaluate TMT's impact. While quantitative data measured performance outcomes, qualitative analysis through open-ended questionnaires revealed crucial subjective dimensions of the learning process. Thematic analysis followed Braun & Clarke's [47] six-phase framework:

As shown in Table 1, the qualitative analysis of questionnaire data identified five key themes in line with Constructivist principles. A substantial 78.38% of students reported actively building vocabulary through TMT's interactive quizzes and discussions, reflecting the active construction principle. This high frequency of Active Lexical Construction validates TMT's success in implementing Piaget's equilibration theory via adaptive difficulty algorithms.

Over half (56.08%) of the students noted increased interest and motivation due to engaging in activities, which is related to self-regulation and intrinsic motivation [48]. Teamwork ability was enhanced for 45.27% of students through group work, aligning with social interactivity and Vygotsky's zone of proximal development (ZPD). Collaborative meaning-making patterns in 63% of group interactions are in line with Vygotsky's ZPD theory, especially in peer scaffolding dynamics.

Autonomous learning ability improved by 46.62% as TMT encouraged self-directed learning, demonstrating cognitive apprenticeship. Additionally, 51.35% of students could apply vocabulary to real-life situations, underscoring situated cognition, and confirming the system's ecological validity. Overall, TMT has a positive impact on vocabulary learning and related aspects within the Constructivist framework.

Table 1. Key themes from questionnaire data based on constructivism

Theme	Frequency (%)	Example Quote	Constructivist Aspect
Active Lexical Construction	78.38	"TMT's interactive quizzes forced me to actively rebuild word meanings"	Piaget's Schema Adaptation
Motivational Scaffolding	56.08	"TMT's real-time encouragement made me persist through challenges"	Vygotsky's Affective Filter Theory
Collaborative Meaning-Making	45.27	"Peer debates in TMT's discussion clarified polysemous word usage contexts"	Social Constructivism (Wertsch)
Metacognitive Regulation	46.62	"Classroom discussion of TMT helped me identify more vocabulary memory methods"	Active Learning
Situated Application	51.35	"Daily Quick Answer of TMT let me test newly learned culinary terms in real-time situations"	Lave & Wenger's Situated Learning

Quantitative Analysis, qualitative analysis yielded clear results demonstrating the positive functions and impacts of TMT on students within the Constructivist framework. Subsequently, a quantitative analysis was carried out. First, descriptive analysis was employed to compare the academic disparities between the experimental and control groups. Furthermore, factor analysis and regression analysis were conducted to precisely probe into the relationship between the utilization of TMT and vocabulary augmentation.

Descriptive Analysis, After a semester, 144 students took the final exam with sections on word matching (testing retention), word and language usage (application and grammar), reading comprehension (information extraction, reasoning, summarizing), translation (bilingual conversion), and writing (various styles). Focusing on vocabulary-related achievements, we collected the scores and used SPSS V.29 for descriptive analysis, followed by a comparison between the control and experimental groups.

As depicted in Table 2, a descriptive analysis was conducted via SPSS V.29 on the comprehensive scores of the students from the control group. Regarding the Total Scores, the mean value was 44.785 (out of 100 in total), with a standard deviation of 16.9701 and a variance of 287.985. This indicates that the students in the control group exhibited a relatively low average academic performance, and there was a high dispersion in the overall academic performance in the absence of Teacher-mate (TMT). In terms of the word matching section, the mean was 6.08 (out of 10). When considering the Language Usage part, the mean was 7.25 (out of 15).

Table 3 details a descriptive analysis via SPSS V.29 of the experimental group's comprehensive scores. The experimental group had a Total Score mean of 55.74 (out of 100), about 11 points higher than the control group's 44.785, evidencing overall superiority in word-related tasks [49]. Also, with a standard deviation of 14.900 and a variance of 222.000, both lower than the control group's, its performance was more stable.

Table 2. The results of the final examination of the control group

		Words Matching	Words in Use	Language Usage	Reading comprehension	Translation	Writing	Total
N	Valid	72	72	72	72	72	72	72
	Missing	0	0	0	0	0	0	0
Mean		6.08	3.25	7.25	13.22	9.563	5.42	44.785
Std. Deviation		2.996	3.179	2.807	5.662	6.5558	3.823	16.9701
Variance		8.979	10.106	7.88	32.063	42.978	14.613	287.985

Table 3. The results of the final examination of the experimental group

		Words Matching	Words in Use	Language Usage	Reading comprehension	Translation	Writing	Total
N	Valid	72	72	72	72	72	72	72
	Missing	0	0	0	0	0	0	0
Mean		8.15	2.72	9.58	15.53	10.93	8.82	55.74
Std. Deviation		2.62	2.451	2.689	6.112	5.439	3.905	14.9
Variance		6.864	6.006	7.232	37.351	29.587	15.249	222

Regarding specific components, the experimental group outperformed the control group. It had a mean of 8.15 in word matching (versus 6.08 for the control group), showing better vocabulary memorization, and a mean of 9.58 in language usage (versus 7.25), indicating a stronger grasp of vocabulary and related grammar.

These results align with Constructivist principles. The TMT-enabled active learning environment likely promoted knowledge internalization and application, leading to enhanced vocabulary-related performance in the experimental group [50].

Chi-square Tests, Subsequent to the descriptive analysis, it has become evident that the mean academic performance of the experimental group, wherein Teacher-mate (TMT) was utilized, surpassed that of the control group under traditional teaching without TMT. Subsequently, Chi-square tests were conducted to explore the association between the application of TMT and students' vocabulary memory.

Table 4 presents the Chi-square test results for the relationship between TMT utilization and word-matching scores. The null hypothesis of no association between TMT usage and word-matching performance was rejected, given the p-value < 0.001. This shows TMT usage has a significantly positive impact on word-matching, which reflects vocabulary memory. Our finding aligns with Nurmala [51], suggesting TMT benefits word-matching performance, likely by enhancing vocabulary memory-related learning experiences.

Table 4. Chi-square tests between TMT usage and words matching results

Aspect	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	30.359[a]	10	< 0.001
Likelihood Ratio	32.863	10	< 0.001
Linear-by-Linear Association	17.238	1	< 0.001
N of Valid Cases	144		

a. 12 cells (54.5%) have expected count less than 5. The minimum expected count is 1.50.

A similar Chi-square test for TMT usage and language usage academic performance also rejected the null hypothesis of independence (p-value < 0.001). Thus, TMT usage positively affects language usage performance, which assesses vocabulary understanding and application. Word-matching focuses on vocabulary-meaning memorization, while language usage emphasizes understanding and applying vocabulary. Based on the Constructivism theory, where learning is an active knowledge-construction process, TMT likely positively influences students' vocabulary-related learning. By promoting active engagement, TMT aids students in constructing new vocabulary knowledge.

Table 5. Chi-square tests for TMT usage and overall academic performance

	Value	df	Asymptotic Significance (2-sided)
Pearson Chi-Square	75.295[a]	59	0.075
Likelihood Ratio	100.815	59	< 0.001
Linear-by-Linear Association	15.235	1	< 0.001
N of Valid Cases	144		

a: 12 cells (54.5%) have expected count less than 5. The minimum expected count is 1.50.

As shown in Table 5, a Chi-square test was performed to explore the relationship between TMT usage and students' overall academic performance. The null hypothesis posited that TMT usage and total scores were independent. The results revealed a p-value of ≤ 0.075 yet > 0.05, meaning the null hypothesis could not be rejected. Thus, while TMT significantly boosts word matching and language usage, it doesn't greatly affect total scores. Chi-square tests also showed that TMT had a positive impact on writing and translation (p-value < 0.01 and 0.013, respectively), but not on reading comprehension (p-value = 0.589 > 0.05). This indicates that TMT aids vocabulary memorization and application, benefiting writing and translation [52]. However, reading comprehension, requiring logical training and techniques [53], isn't significantly influenced by TMT. Given that reading comprehension accounts for nearly one-third of the total score, the link between TMT usage and overall academic performance is weak.

Factor Analysis, before commencing the regression analysis, a factor analysis was systematically implemented. In the context of exploring the impact of Teacher-mate Technology (TMT) on vocabulary learning, such an analysis was crucial as it could streamline the complex set of variables related to vocabulary skills. The overarching objective was to assess whether Words Matching, which reflects vocabulary retention, Words in Use, representing vocabulary application, and Language Usage, indicating vocabulary adaptation, could be amalgamated into a unified composite variable. By achieving this integration, a more holistic and in-depth analysis could be executed. This would not only simplify the analytical process but also facilitate a more precise elucidation of the intricate relationship between TMT usage and vocabulary augmentation.

Table 6. Component Matrixa[a] of factor analysis

Component Matrixa[a]	
	Component 1
Words Matching	0.763
Words in Use	0.758
Language Usage	0.709
Extraction Method: Principal Component Analysis.	

a: 1 components extracted.

Table 6 shows the proportion of each variable's variance that can be explained by the extracted components. The initial values for all variables (Words Matching, Words in Use, Language Usage) are 1.000, indicating that the full variance of each variable is considered in the initial model. The extraction values are as follows: Words Matching (0.582), Words in Use (0.574), and Language Usage (0.502). These values suggest that the extracted components explain approximately 58.2%, 57.4%, and 50.2% of the variance for Words Matching, Words in Use, and Language Usage, respectively. This indicates a moderate to high level of explained variance for these variables, suggesting that the extracted components are capturing a significant portion of the variability in the data.

Table 7. KMO and Bartlett's test of factor analysis

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.633
Bartlett's Test of Sphericity	Approx. Chi-Square	41.917
	df	3
	Sig.	< 0.001

As shown in Table 7, the KMO value is 0.633. Generally, a KMO value greater than 0.5 indicates that the data is suitable for factor analysis. This value suggests that the correlations among variables are acceptable. The Bartlett's Test of Sphericity has an Approx. Chi-square value of 41.917 with 3 degrees of freedom, and the significance level is less than 0.001. This indicates that the correlation coefficient matrix is not an identity matrix, meaning that there are correlations among the variables, which also supports the conduct of factor analysis.

Overall, the communalities showing moderate-to-high explained variance, a KMO value of 0.633 (above the 0.5 threshold), and a significant Bartlett's Test of Sphericity result all indicate that it is feasible to integrate Words Matching (vocabulary retention), Words in Use (vocabulary application), and Language Usage (vocabulary adaptation) into a combined variable through factor analysis.

Regression Analysis, by conducting a factor analysis, we derived a new variable named "vocabulary ability" to represent the capabilities of vocabulary retention, application, and adaptation. Subsequently, we performed a further regression analysis to examine the relationship between the use of TMT and this new variable, "Vocabulary ability", with the aim of exploring the precise impact of TMT on vocabulary ability.

Table 8. ANOVA of regression analysis

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11.623	1	11.623	12.563	< 0.001[b]
	Residual	131.377	142	0.925		
	Total	143	143			

a: Dependent Variable: Vocabularyability
b: Predictors: (Constant), The usage of Teacher-mate

The overall significance of the model is indicated by the F-statistic in Table 8, which is 12.563, and the corresponding significance level (Sig.) is less than 0.001. This suggests that the regression model is highly significant in a statistical sense. In other words, the independent variable "Use of Teacher-mate", together with the constant term, has a significant explanatory power over the dependent variable "Vocabulary Ability". This result leads to the rejection of the null hypothesis that the independent variable has no effect on the dependent variable.

The significance of the coefficients is shown in the Table 9. The constant term has a coefficient of −0.284, a t-value of −2.506, and a significance level (Sig.) of 0.013, which is less than 0.05. This indicates that the constant term is significant in the model. The unstandardized coefficient B for the independent variable "Use of Teacher-mate" is 0.568, meaning that for every one-unit increase in this variable, the dependent variable "Vocabulary Ability" increases by an average of 0.568 units. The standardized coefficient Beta is 0.285, the t-value is 3.544, and the significance level (Sig.) is less than 0.001. This shows that the impact of this independent variable on the dependent variable is not only positive in direction but also highly significant in a statistical sense.

The model summary presented in Table 10 indicates a weak linear relationship between "Use of Teacher-mate" (independent variable) and "Vocabulary Ability" (dependent variable), with R = 0.285, R Square = 0.081, and adjusted R Square = 0.075. These values suggest that only 8.1% of the variance in vocabulary ability is explained by the model, highlighting its limited explanatory power. Regression results confirm a statistically significant positive effect of "Use of Teacher-mate" (B = 0.568, β = 0.285, t = 3.544, p < 0.001), supported by the model's significance (F = 12.563, p < 0.001). However, the low R Square implies that critical factors such as prior vocabulary knowledge, learning motivation, and instructional methods are likely omitted. This aligns with research emphasizing the multifactorial nature of language skill development, where isolated technological interventions rarely account for complex learning dynamics [54].

Table 9. The results of coefficients[a]

Model		Unstandardized B	Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	−0.284	0.113		−2.506	0.013
	The usage of Teacher-mate	0.568	0.16	0.285	3.544	< 0.001

a: Dependent Variable: Vocabularyability

Table 10. The results of model summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	Change Statistics			
						F Change	df1	df2	Sig. F Change
1	0.285[a]	0.081	0.075	0.96186726	0.081	12.563	1	142	< 0.001

a: Predictors: (Constant), The usage of Teacher-mate

b: Dependent Variable: Vocabularyability

C. Discussion and Findings

Based on the Cognitive-Constructivist theory and in combination with the application of TMT, following a semester-long experiment and research, we conducted descriptive and statistical analyses of the data collected from students. Eventually, we arrived at conclusions regarding the research questions.

Q1: What is the rationale behind the TMT-enhanced vocabulary learning process? The rationale for TMT-enhanced vocabulary learning is rooted in Cognitive-Constructivist principles. Interactive quizzes promote active knowledge construction by engaging learners in assimilating polysemous vocabulary (e.g., "book" as noun/verb) through immediate feedback, aligning with Piaget's emphasis on cognitive adaptation. Collaborative discussions via TMT foster social interaction, enabling multi-perspective analysis of lexical nuances within Vygotsky's Zone of Proximal Development. Simultaneously, TMT's data-driven analytics support situated and personalized learning by tailoring feedback and pathways to individual needs, reflecting scaffolded instruction in contextualized settings. These mechanisms collectively operationalize Constructivist tenets, positioning learners as active agents in vocabulary acquisition.

Q2: What is the association between the utilization of the TMT and students' English vocabulary learning outcomes? Quantitative analyses confirm a statistically significant positive association between TMT usage and vocabulary learning outcomes. The experimental group demonstrated superior vocabulary retention in matching tasks (M = 8.15 vs. control M = 6.08; p < 0.001), consistent with technology-enhanced lexical retention mechanisms [55]. Regression analysis further revealed TMT's predictive effect on vocabulary application (β = 0.285, p < 0.001), supported by higher contextualized task performance (M = 9.58 vs. 7.25), aligning with evidence on interactive tools' role in lexical skill transfer. Additionally, 78.38% of learners reported heightened engagement, reflecting TMT's alignment with Constructivist principles of self-directed learning. These findings collectively underscore TMT's efficacy in fostering active vocabulary acquisition while highlighting its dependency on learner participation.

Q3: Does TMT have a similarly obvious positive impact on students' vocabulary memory and comprehensive academic performance? TMT exhibits dual roles in language learning: it effectively enhances vocabulary dependent skills (writing: p < 0.01; translation: p = 0.013) via lexical retrieval (R^2 = 8.1%), yet underperforms in reading comprehension (p = 0.589). This aligns with critiques of tool-centric approaches [56] and mirrors Johnson *et al.*'s [57] finding that vocabulary tools often lack explicit higher-order strategy training (e.g., inferencing, $d = 0.62$). To bridge this gap, TMT should integrate schema-building tasks (e.g., linking vocabulary to contextual inferences) and metacognitive dashboards for self-regulated learning. Concurrently, TMT fosters cultural-semantic innovation—learners negotiating polysemy (e.g., "bank" as finance vs. geography) exhibit translanguaging dynamics [58], advancing pragmatic competence. However, maximizing this potential requires synergizing cultural-semantic debates with Johnson *et al.*'s cognitive frameworks, transforming TMT into a hybrid system that cultivates both lexical precision and critical analysis.

V. Conclusion

This study validates TMT's alignment with cognitive-constructivist principles, enhancing vocabulary retention ($p < 0.001$) and application ($\beta = 0.285$, $p < 0.001$) through interactive quizzes and social negotiation. However, its limited impact on reading comprehension ($p = 0.589$) and holistic academic gains ($R^2 = 8.1\%$) exposes a critical gap in scaffolding higher-order skills like inferential reasoning. Importantly, TMT also drives cultural-semantic innovation: learners decoding polysemy (e.g., "bank" as finance/geography) exhibit translanguaging dynamics, advancing pragmatic competence. To bridge lexical and cognitive divides, future TMT systems should integrate these cultural negotiations with evidence-based strategies for critical analysis, fostering both vocabulary mastery and text-level reasoning.

The findings yield actionable implications for optimizing vocabulary instruction and technology integration. Educators should strategically harness TMT's strengths—interactive quizzes and adaptive feedback—to bolster core vocabulary skills, while integrating it with explicit critical reading instruction (e.g., contextual inference) to offset its limitations in higher-order competencies. Concurrently, teacher training must prioritize data-driven adaptation of TMT analytics to personalize scaffolding, ensuring alignment with learners' evolving needs. Institutionally, curricula should embed TMT as a supplementary tool within frameworks like CEFR, balancing technological efficiency with traditional pedagogy to holistically cultivate lexical precision, analytical reasoning, and cross-cultural communication—a hybrid model mitigating tech-overreliance while maximizing targeted skill development.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Pengbiao Zhang conceived the concept, carried out the data analysis, and authored the paper. Fengjunzi Wang conducted the research, administered the project, and oversaw the editing and review process. All authors gave their approval for the final version.

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