Journal of Innovation & Knowledge 10 (2025) 100641

Contents lists available at ScienceDirect

Journal of Innovation & Knowledge

journal homepage: www.elsevier.com/locate/jik

Innovative interactive instruction to enhance learning behaviors

Duen-Huang Huang

Center for Teacher Education, Chaoyang University of Technology, 168, Jifeng E. Rd., Wufeng District, Taichung, 413310, Taiwan, ROC

ARTICLE INFO

JEL classification:
I230
I210

Keywords:
Cooperative learning
Multimodel interactive teaching program
Problem based learning
Technology acceptance model

ABSTRACT

This study applies the Technology Acceptance Model to examine user acceptance of emerging technologies—specifically LINE and Google Translate—for language learning. A multimodal interactive teaching program, combining cooperative learning and problem-based learning, was implemented at a university in Taiwan. Upon completion, a survey was conducted among participating students. Factor loading analysis reveal strong correlations between the variables and their corresponding constructs. Reliability tests confirm the internal consistency of the questionnaire, while confirmatory factor analysis validates the convergent validity of all constructs. The study also uncovered departmental differences in technology acceptance behavior, and the results indicated significant improvements in both learning motivation and student attitudes.

Introduction

In today's rapidly evolving educational landscape, traditional teaching methodologies are increasingly being challenged by the changing needs and preferences of students, particularly Generation Z learners. Conventional classroom instruction often falls short in engaging students and adapting to their shifting learning patterns. To address these challenges, integrating technology with innovative teaching strategies has become essential for enhancing both student engagement and academic performance. Notably, innovative teaching is increasingly recognized as part of universities' social responsibility (de Moraes Abrahão et al., 2024; Shek et al., 2017).

One promising approach is multimodal interactive teaching, which combines various instructional methods to create a dynamic and engaging learning environment. For example, Song (2024) utilizes social network analysis to design interactive learning frameworks that significantly improve learning outcomes. Additionally, cooperative learning techniques and problem-based learning (PBL) are often integrated into multimodal teaching, fostering critical thinking and collaborative experiences (Hidayati et al., 2022; Saiful et al., 2020).

This study investigates how college students adopt new technologies in their learning processes and how these technologies influence their motivation and attitudes toward learning. The Technology Acceptance Model (TAM) provides a framework for analyzing students' acceptance of digital tools, including social media platforms (e.g., LINE) and learning tools (e.g., Google Translate), particularly in the context of language learning. Over the course of one year, multimodal interactive teaching was implemented for a group of college students. At the end of the study, a survey involving 202 participants was conducted. The empirical findings offer valuable insights into students' perceptions and acceptance of technology within this innovative teaching framework.

To further examine the impact of innovative teaching on learning behaviors, this study addresses the following research questions (RQs):

RQ1: How do the perceived ease of use and usefulness of artificial intelligence (AI)-powered tools influence students' attitudes toward language learning?

RQ2: Do students from different academic disciplines demonstrate varying levels of technology acceptance in a multimodal interactive learning environment?

RQ3: What roles do cooperative learning and problem-based learning play in enhancing students' acceptance of technology?

The remainder of this paper is structured as follows. Section 2 reviews relevant literature on various teaching methods and the TAM framework. Section 3 outlines the teaching design, focusing on guiding students to understand the impact of AI across different domains. Section 4 details the objectives, scope, participants, methods, and data analysis techniques used to evaluate the teaching approach's effectiveness. Section 5 presents findings related to students' learning attitudes, motivations, and technology acceptance. Section 6 discusses implications for educators and students. Section 7 concludes the study and offers recommendations based on the key findings.

E-mail address: dhhuang@cyut.edu.tw.

https://doi.org/10.1016/j.jik.2024.100641
Received 24 August 2024; Accepted 5 December 2024
Available online 12 December 2024

Research background

Evolution of teaching methods

Traditional classroom teaching, which relies heavily on teacher-led instruction, often struggles to maintain students' attention despite significant effort. As learning resources expand beyond textbooks, Generation Z students exhibit evolving learning patterns. The advancement of information and communication technologies has diversified teaching tools, fostering enhanced interaction between educators and learners and making learning more engaging (Betihavas et al., 2016).

Blankesteijn et al. (2024) underscore the significance of experiential learning in science- and technology-based entrepreneurship education, identifying four core activities: incorporating real-world experiences into the classroom, recognizing the complexity of management and entrepreneurial challenges, engaging students in management interventions, and emphasizing the value of reflection. Similarly, Wu and Chen (2021) demonstrate the effectiveness of experiential and constructivist learning approaches in courses such as innovation management, knowledge management, project management, and risk management, particularly within business schools.

To improve academic performance and student satisfaction, Song (2024) introduces a multimodal interactive classroom strategy based on social network analysis. The findings indicate that this approach enhances academic outcomes and student satisfaction. In this context, that study applies cooperative learning, which Slavin (1987)) describes as a method where students work in small, mixed-ability groups to achieve common learning goals. Taghizadeh and Hajhosseini (2021) show that blended learning technologies positively influence student attitudes by enabling instructors to teach both theoretical and practical concepts effectively while fostering online discussions with constructive feedback. Cooperative learning structures group interactions to ensure active participation and accountability (Sharan & Sharan, 2021) while building collaborative learning environments (Johnson & Johnson, 2018).

Critical thinking (CT) has been shown to significantly enhance academic performance, particularly for Master of Business Administration and undergraduate students (D'Alessio et al., 2019; Fong et al., 2017). CT skills are also instrumental in driving workplace effectiveness and innovation (Jafarigohar et al., 2016; Li, 2023). Problem-based learning (PBL) is a proven method for developing CT, as it emphasizes real-world problem-solving. By encouraging students to work in groups to address real-world challenges, PBL promotes critical thinking, collaboration, and self-directed learning (Akhdinirwanto et al., 2020; Foo et al., 2021).

Technology continues to play an increasingly central role in higher education, including the integration of social media (Aldahdouh et al., 2020; Tan & Hsu, 2018). Al-Qaysi et al. (2023) highlight the potential of social media to foster collaboration and communication. Likewise, Davidovitch and Belichenko (2018) find that the use of appropriate learning tools positively impacts learning and satisfaction, with group belongingness being a critical factor. A sense of belonging enhances interactions and alleviates the isolation often associated with distance learning environments (Callaghan & Fribbance, 2016; Sheeran & Cummings, 2018). Even passive interactions within online groups can strengthen course commitment, a key aspect of distance learning success (Giannikas, 2020; Moghavvemi et al., 2017; Moorthy et al., 2019).

Technology acceptance model

The TAM, developed by Davis et al. (1989), provides a theoretical framework for understanding how users adopt new technologies. It is centered on two key constructs: perceived usefulness (PU) and perceived ease of use (PEOU). PU refers to users' belief that using a particular technology will enhance their performance, reflecting the technology's value in achieving their goals. PEOU, on the other hand, reflects users' perception of how easy the technology is to use. Technologies perceived as both useful and easy to use are more likely to be adopted. These constructs influence users' attitudes toward the technology, which, in turn, shape their intention to use it.

TAM has been widely applied and extended to predict technology adoption across various contexts. For example, Huang and Chueh (2021) expand TAM to develop a model predicting pet owners' intentions to use chatbots for veterinary consultations, aiming to improve pet healthcare and disease management. Similarly, Yao et al. (2022) integrate TAM with the Theory of Planned Behavior to examine college students' intentions to use online learning during the COVID-19 pandemic. Kwangsawad and Jattamart (2022) also apply TAM to evaluate the adoption of chatbots for customer service.

Teaching design

Objectives

The primary objective of this course is to help students understand the potential impact of AI on future life as technology continues to evolve and explore its applications across various fields. By using Google AI-powered translation tools for English vocabulary searches and pronunciation support, students learned to integrate these technologies into their professional English language studies.

Group discussions and collaborations on course-related assignments were facilitated through the LINE social media platform. Students applied foundational digital technology knowledge to gain a deeper understanding of modern industry development trends, while also enhancing their awareness of applied knowledge in areas such as AI, cloud computing, and big data.

Teaching methods

The course was structured into thematic units, integrating group cooperative learning and problem-based learning (PBL) discussions, guided by relevant theoretical principles. Each unit featured lectures on AI, with a focus on commonly used English vocabulary related to AI topics.

A combination of interactive teaching methods and experiential classroom activities enabled students to share diverse practical experiences in group settings. Instruction was tailored to align with the course objectives, students' learning conditions, and contemporary educational needs. A key goal was to enhance students' international perspectives, supporting the Taiwan government's vision of creating a bilingual nation by 2030.

The course also aimed to train students in the use of technological tools, such as Google Translate, for real-time vocabulary queries and voice playback. This approach fostered active learning and imitation, helping students acquire AI-related knowledge while strengthening their English vocabulary comprehension and retention. Through consistent practice, students improved their English language proficiency, expanded their international mobility, and enhanced their professional competence and future career prospects.

Post-class discussions were facilitated through the LINE platform, encouraging students to actively engage with peers and instructors. During class sessions, students were encouraged to use smartphones, tablets, or laptops to search for AI-related vocabulary using Google Translate. Formative assessments, in the form of group presentations, were conducted to evaluate students' understanding and their ability to apply knowledge in meaningful ways.

Research design

Research scope

This study focuses on integrating AI, a key component of cutting-edge global technological advancements, into the learning process.

The course emphasized specialized English vocabulary related to AI, aiming to enhance students' understanding of AI concepts within the context of their professional development.

In-class activities were designed to introduce students to commonly used AI-related English terms. The instructor facilitated these sessions by presenting questions and leading discussions around the vocabulary, encouraging active engagement. This approach aimed to strengthen students' familiarity with AI terminology and concepts, equipping them with the linguistic and conceptual tools necessary for success in modern professional environments.

Research subjects and field

The course, titled Information and Communication Technology with AI Applications, was a compulsory 2-credit general education course. This research focused on students from various departments and grade levels across the university who enrolled in the course.

Prior to the start of the research, students were provided with a comprehensive overview of the course objectives, teaching regulations, syllabus, schedule, and detailed course procedures. This ensured that students had a clear understanding of what to expect and how the course would be conducted.

The course was conducted in two separate sessions, each spanning one academic semester.

First Session (September 2022–January 2023): Enrolled students were from the Department of Communication Arts and the Department of Environmental Engineering and Management.

Second Session (February 2023–July 2023): Enrolled students were from the Department of Leisure Services Management and the Department of Business Administration.

Each session consisted of two lecture-based courses designed to cater to the needs of students from these diverse academic disciplines.

Research framework

To address the research questions, this study employs the TAM as its theoretical foundation and develops the following hypotheses. For RQ1, we propose hypotheses H1 to H5.

H1: PEOU positively influences PU.

H2: PU positively influences UA toward technology.

H3: PEOU positively influences UA toward technology.

H4: PU positively influences UI to use the technology.

H5: UA positively influences UI to use the technology.

These relationships are depicted in Fig. 1, illustrating the interactions among the TAM constructs.

For RQ2, the study examines whether technology acceptance behaviors vary across academic disciplines. The hypothesis is:

H6: Different academic disciplines exhibit varying behaviors in relation to TAM.

For RQ3, the study investigates the impact of cooperative learning and PBL on students' motivation and attitudes toward technology. The hypothesis is:

H7: Cooperative learning and PBL significantly enhance students' learning motivation and attitudes toward technology.

Data collection

This study involved a total of 202 participants ($N = 202$) from various academic departments, distributed as follows:

60 students from the Department of Communication Arts,

54 students from the Department of Environmental Engineering and Management,

38 students from the Department of Leisure Services Management, and

50 students from the Department of Business Administration.

Data were collected using a structured questionnaire, which is provided in Appendix I. The responses were coded and analyzed using SPSS for Windows, enabling the examination of relationships between the variables identified in the research framework.

Empirical analysis

TAM analysis

Following the implementation of the multimodal interactive teaching method, a survey was conducted to test the TAM by gathering and analyzing data. The analysis included factor analysis for factor loadings, reliability testing to measure consistency, confirmatory factor analysis (CFA) to assess convergent validity, and linear regression to evaluate path coefficients.

In factor analysis, factor loadings represent the correlation between observed variables and latent constructs. Factor loadings of 0.70 or higher indicate a strong correlation between a variable and its construct and signify a significant contribution of the variable to the construct.

Reliability testing measures internal consistency of the variables. Composite Reliability (CR) is used in factor analysis and structural

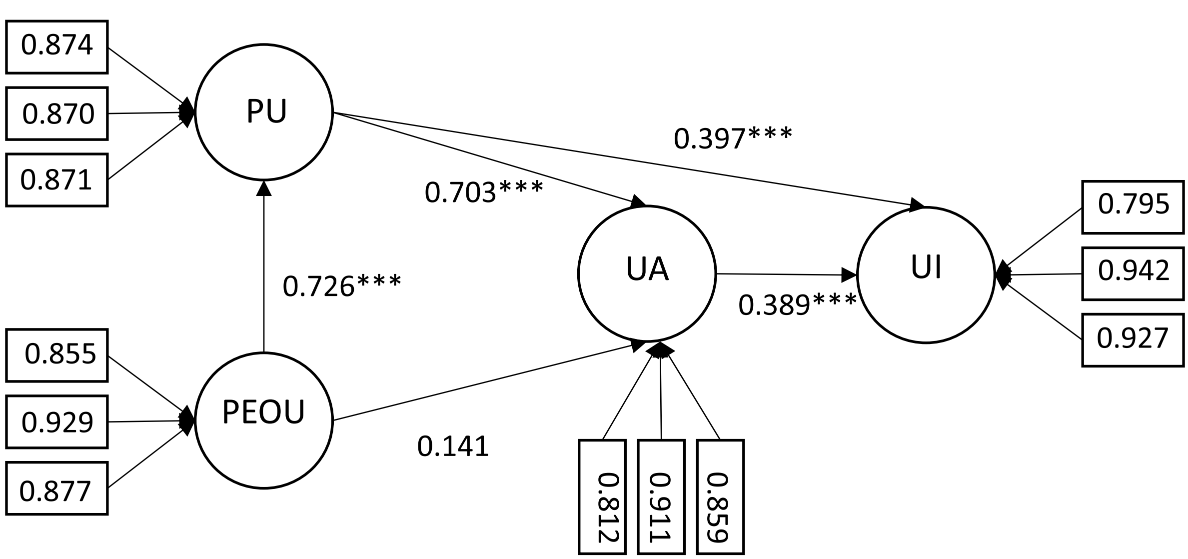

Fig. 1. Research framework.

equation modeling to assess reliability. A CR value of 0.70 or higher indicates good reliability.

In CFA the average variance extracted (AVE) assesses convergent validity. An AVE value of 0.50 or higher indicates that the construct explains a significant portion of the variance in its variables.

Table 1 presents the analysis results for all students, showing strong factor loadings (all above 0.7). For example, the loadings for PU1, PU2, and PU3 are 0.874, 0.870, and 0.871, respectively. The CR value for PU is 0.905, and its AVE is 0.760, demonstrating strong reliability and convergent validity. Across all students, the CR values exceed 0.8, and the AVE values are greater than 0.7, supporting the internal consistency and validity of the constructs.

Tables 2–5 present similar results for each department, with factor loadings predominantly exceeding 0.7, CR values surpassing 0.8, and AVE values above 0.5. These findings indicate that the model is robust for all students and each department.

The regression analysis revealed consistent results across all students and departments (see Tables 1–5). Key paths, such as PU → UA, PU → UI, PEOU → PU, and UA → UI, were significantly positive. However, the path PEOU → UA showed no significance, with some coefficients being positive and others negative. Fig. 1 illustrates all paths and their respective coefficients, providing a visual representation of the relationships within the TAM framework.

Differences in technology acceptance by department

To evaluate Hypothesis 6, pairwise comparisons of path coefficients across departments were conducted. Table 6 summarizes the statistical findings. The results indicate that certain paths, such as PU → UA and PEOU → PU, exhibit no significant differences in path coefficients between departments, suggesting consistent behavior in these relationships across disciplines.

However, significant differences were observed in other paths. Specifically, students from the Department of Communication Arts and the Department of Leisure Services Management demonstrated notable variation in the following paths: PEOU → UA, PU → UI, and UA → UI.

These findings highlight that students' academic disciplines can influence their technology acceptance behaviors, particularly in how ease of use and attitudes shape their intentions to adopt technology. This suggests that tailored instructional strategies may be necessary to accommodate these disciplinary differences.

Table 1
Analysis results (all students)

	Variable	Factor loading	CR	AVE
PU	PU1	0.874	0.905	0.760
	PU2	0.870		
	PU3	0.871		
PEOU	PEOU1	0.855	0.917	0.787
	PEOU2	0.929		
	PEOU3	0.877		
UA	UA1	0.812	0.896	0.742
	UA2	0.911		
	UA3	0.859		
UI	UI1	0.795	0.920	0.792
	UI2	0.942		
	UI3	0.927		

Path	Coefficient	T value
PU -> UA	0.703	7.393***
PU -> UI	0.397	10.519***
PEOU -> PU	0.726	10.482***
PEOU -> UA	0.141	1.677
UA -> UI	0.389	10.519***

Table 2
Analysis results (Department of Communication Arts)

	Variable	Factor loading	CR	AVE
PU	PU1	0.915	0.942	0.844
	PU2	0.901		
	PU3	0.939		
PEOU	PEOU1	0.841	0.953	0.872
	PEOU2	0.934		
	PEOU3	0.889		
UA	UA1	0.874	0.918	0.790
	UA2	0.948		
	UA3	0.871		
UI	UI1	0.813	0.938	0.835
	UI2	0.951		
	UI3	0.970		

Path	Coefficient	T Value
PU -> UA	0.921	4.755**
PU -> UI	0.455	6.955***
PEOU -> PU	0.781	7.047***
PEOU -> UA	-0.251	-1.381
UA -> UI	0.419	6.955***

Table 3
Analysis results (Department of Environment Engineering and Management)

	Variable	Factor loading	CR	AVE
PU	PU1	0.925	0.883	0.718
	PU2	0.856		
	PU3	0.752		
PEOU	PEOU1	0.811	0.878	0.707
	PEOU2	0.941		
	PEOU3	0.760		
UA	UA1	0.745	0.870	0.692
	UA2	0.888		
	UA3	0.856		
UI	UI1	0.706	0.887	0.726
	UI2	0.920		
	UI3	0.913		

Path	Coefficient	T Value
PU -> UA	0.688	4.063**
PU -> UI	0.260	3.077**
PEOU -> PU	0.433	2.689**
PEOU -> UA	0.243	1.926
UA -> UI	0.254	3.077**

Table 4
Analysis results (Department of Leisure Services Management)

	Variable	Factor loading	CR	AVE
PU	PU1	0.916	0.952	0.870
	PU2	0.909		
	PU3	0.972		
PEOU	PEOU1	0.887	0.953	0.872
	PEOU2	0.976		
	PEOU3	0.936		
UA	UA1	0.949	0.832	0.820
	UA2	0.896		
	UA3	0.870		
UI	UI1	0.934	0.967	0.907
	UI2	0.966		
	UI3	0.957		

Path	Coefficient	T Value
PU -> UA	0.577	2.963**
PU -> UI	0.419	6.627***
PEOU -> PU	0.778	5.663***
PEOU -> UA	0.298	1.560
UA -> UI	0.442	6.627***

Table 5
Analysis results (Department of Business Administration)

	Variable	Factor loading	CR	AVE
PU	PU1	0.751	0.850	0.651
	PU2	0.849		
	PU3	0.818		
PEOU	PEOU1	0.903	0.963	0.809
	PEOU2	0.898		
	PEOU3	0.897		
UA	UA1	0.646	0.834	0.631
	UA2	0.834		
	UA3	0.883		
UI	UI1	0.798	0.893	0.736
	UI2	0.926		
	UI3	0.846		

Path	Coefficient	T Value
PU -> UA	1.312	4.323***
PU -> UI	0.438	5.745***
PEOU -> PU	0.881	6.396***
PEOU -> UA	-0.371	-0.062
UA -> UI	0.423	5.745***

Learning motivation and attitude

To evaluate the effectiveness of the innovative teaching method, the study employed a single-group pre-test/post-test design to assess changes in learning motivation and attitudes. Table 7 presents paired-sample statistics for pre-test and post-test scores across all students, while Table 8 shows the differences between the pre-test and post-test scores.

Learning motivation was measured across six components: self-efficacy, proactive learning strategies, AI learning value, performance goals, achievement goals, and learning environment stimulation. The average pre-test score was 3.42 (SD = 0.48), and the post-test score was 3.53 (SD = 0.54). A paired-sample t-test reveals a significant improvement ($t = 0.0000$, $p < 0.01$).

Four components show significant improvements between pre- and post-test scores as noted below.

Self-efficacy: Pre-test 3.45, Post-test 3.64 ($t = 4.87$, $p < 0.001$).

AI learning value: Pre-test 3.74, Post-test 3.83 ($t = 2.13$, $p < 0.05$).

Performance goal orientation: Pre-test 3.07, Post-test 3.15 ($t = 2.40$, $p < 0.05$).

Learning environment stimulation: Pre-test 3.20, Post-test 3.35 ($t = 4.13$, $p < 0.001$).

Two components, proactive learning strategies and achievement goals, did not show significant differences, with t-values of 1.80 ($p = 0.073$) and 1.45 ($p = 0.149$), respectively. Regarding learning attitudes, which were assessed across six components (including self-awareness, learning desire, and learning habits), the average pre-test score was 3.21 (SD = 0.52), and the post-test score was 3.31 (SD = 0.56). A paired-sample t-test revealed a significant difference ($t = 0.0000$, $p < 0.05$).

Two components show significant improvements in learning attitudes as follows.

Self-awareness: Pre-test 2.89, Post-test 3.17 ($t = 6.88$, $p < 0.001$).

Learning habits: Pre-test 3.09, Post-test 3.18 ($t = 2.10$, $p < 0.05$).

Four components, including learning desire and learning process, did not show significant differences. However, the self-awareness component exhibited a highly significant improvement, indicating a deeper understanding of AI concepts and competencies. Further insights could be gained by calculating the effect size for these findings.

Discussions

Theoretical implication

In educational theory, teaching is often divided into two core

Table 6
Pair-wise comparisons of behaviors in technology acceptance

PU -> UA	Department	Coefficient	P Value
	Business Administration	1.312	0.952
	Communication Arts	0.921	
	Business Administration	1.312	0.476
	Environment Engineering and Management	0.688	
	Business Administration	1.312	0.189
	Leisure Services Management	0.577	
	Communication Arts	0.921	0.498
	Environment Engineering and Management	0.688	
	Communication Arts	0.921	0.196
	Leisure Services Management	0.577	
	Environment Engineering and Management	0.688	0.518
	Leisure Services Management	0.577	
PEOU -> UA	Department	Coefficient	P Value
	Business Administration	-0.371	0.277
	Communication Arts	-0.251	
	Business Administration	-0.371	0.105
	Environment Engineering and Management	0.243	
	Business Administration	-0.371	0.043*
	Leisure Services Management	0.298	
	Communication Arts	-0.251	0.024*
	Environment Engineering and Management	0.243	
	Communication Arts	-0.251	0.011*
	Leisure Services Management	0.298	
	Environment Engineering and Management	0.243	0.526
	Leisure Services Management	0.298	
PEOU -> PU	Department	Coefficient	P Value
	Business Administration	0.881	0.274
	Communication Arts	0.781	
	Business Administration	0.881	0.265
	Environment Engineering and Management	0.433	
	Business Administration	0.881	0.681
	Leisure Services Management	0.771	
	Communication Arts	0.781	0.069
	Environment Engineering and Management	0.433	
	Communication Arts	0.781	0.533
	Leisure Services Management	0.778	
	Environment Engineering and Management	0.433	0.178
	Leisure Services Management	0.778	
PU -> UI	Department	Coefficient	P Value
	Business Administration	0.438	0.018*
	Communication Arts	0.455	
	Business Administration	0.438	0.056
	Environment Engineering and Management	0.260	
	Business Administration	0.438	0.330
	Leisure Services Management	0.419	
	Communication Arts	0.455	0.474
	Environment Engineering and Management	0.260	
	Communication Arts	0.455	0.000***
	Leisure Services Management	0.419	
	Environment Engineering and Management	0.260	0.044*
	Leisure Services Management	0.419	
UA -> UI	Department	Coefficient	P Value
	Business Administration	0.423	0.010*
	Communication Arts	0.419	
	Business Administration	0.423	0.008**
	Environment Engineering and Management	0.254	
	Business Administration	0.423	0.645
	Leisure Services Management	0.442	
	Communication Arts	0.419	0.474
	Environment Engineering and Management	0.254	
	Communication Arts	0.419	0.000***

(*continued on next page*)

Table 6 (*continued*)

Leisure Services Management	0.442	
Environment Engineering and Management	0.254	0.005**
Leisure Services Management	0.442	

components: instructional materials and teaching methods. A significant challenge for educators lies in effectively enhancing students' learning motivation and attitudes. When facing difficulties during teaching, one strategic solution is to adjust either the instructional materials or the teaching methods. With the rapid pace of technological advancement and the widespread application of AI, introducing cutting-edge knowledge into the classroom and employing innovative teaching techniques have become even more crucial.

Based on the empirical findings of this study, most of the paths in the TAM were supported, except for the path PEOU → UA. This suggests that TAM remains to be a relevant framework for explaining technology acceptance within a multimodal interactive teaching environment at the university level. However, the lack of support for the path PEOU → UA, observed consistently across student groups and departments, can be explained by two potential reasons:

Higher Perceived Value: The students may perceive the combined use of LINE and Google Translate as so valuable that it outweighs any difficulties in ease of use, leading them to overcome any challenges in learning both applications.

Ease of Use Not Salient: Both LINE and Google Translate may already be perceived as easy to use, rendering perceived ease of use less relevant in influencing students' attitudes toward the apps.

Furthermore, the study finds significant differences in the technology acceptance behaviors of students from different departments. This suggests that when applying diverse teaching methods, educators should be mindful of the distinct behaviors linked to students' academic backgrounds. Understanding these differences is key to customizing teaching approaches to maximize their effectiveness.

Finally, the significant improvements in learning motivation and attitude, as shown by the pre- and post-test results, affirm that the introduction of innovative teaching methods positively impacts students' learning outcomes. The results of this study highlight the value of utilizing innovative teaching techniques, such as multimodal interactive learning, in enhancing students' technology acceptance, motivation, and attitudes.

Practical implication

From a practical standpoint, emphasizing the importance of AI-related professional English and promoting interactive Q&A sessions offer significant benefits. By encouraging the use of tools like Google Translate and pronunciation apps on smartphones or tablets, students in this study became more inclined to practice reading English aloud, which contributed to improvements in their grades.

Instead of prohibiting the use of mobile phones in the classroom, instructors can incorporate technology as part of the learning process. By designing questions related to course content, students can be encouraged to use their phones for research, which not only makes the learning environment more dynamic and engaging but also gives them access to the latest information online.

The use of LINE groups for discussions, especially during the COVID-19 pandemic when face-to-face interactions were limited, proved both economical and convenient. Students participated in problem-based learning (PBL) through LINE, collaborating on discussions and completing group projects remotely, which enhanced their ability to engage in collaborative learning even in challenging times.

In conclusion, the implementation of a multimodal interactive teaching method significantly enhances the teaching process and students' learning experiences. It improves students' motivation and

Table 7
All student paired sample statistics.

		Mean	Number	Standard Deviation	Standard Error of the Mean
Motivation: Self Efficacy	Pre-test score	3.445	202	.6006	.0423
	Post-test score	3.638	202	.6271	.0441
Motivation: Active Learning Strategy	Pre-test score	3.717	202	.5468	.0385
	Post-test score	3.791	202	.5945	.0418
Motivation: AI Learning Value	Pre-test score	3.740	202	.5165	.0363
	Post-test score	3.834	202	.6778	.0477
Motivation: Performance Goal	Pre-test score	3.069	202	.3714	.0261
	Post-test score	3.147	202	.4370	.0307
Motivation: Achievement Goal	Pre-test score	3.359	202	.4280	.0301
	Post-test score	3.411	202	.4546	.0320
Motivation: Learning Environment Stimulation	Pre-test score	3.200	202	.4355	.0306
	Post-test score	3.345	202	.4668	.0328
Attitude: Self Awareness	Pre-test score	2.891	202	.5456	.0384
	Post-test score	3.174	202	.5609	.0395
Attitude: Learning Desire	Pre-test score	3.521	202	.5789	.0407
	Post-test score	3.559	202	.6248	.0440
Attitude: Learning Method	Pre-test score	3.274	202	.4196	.0295
	Post-test score	3.308	202	.4431	.0312
Attitude: Learning Plan	Pre-test score	2.908	202	.4996	.0352
	Post-test score	2.981	202	.5711	.0402
Attitude: Learning Habit	Pre-test score	3.094	202	.5324	.0375
	Post-test score	3.177	202	.5936	.0418
Attitude: Learning Process	Pre-test score	3.598	202	.5353	.0377
	Post-test score	3.649	202	.5680	.0400

Table 8
All students paired samples t-test (Post-test score - Pre-test score)

	Paired Differences					t	df	Sig. (Two-Sided) p
	Mean	Std Dev	Std Error Mean	95% Confidence Interval of the Difference				
				Lower	Upper			
Motivation: Self Efficacy	.1936	.5645	.0397	.1153	.2719	4.874	201	.000***
Motivation: Active Learning Strategy	.0738	.5815	.0409	-.0069	.1544	1.803	201	.073
Motivation: AI Learning value	.0941	.6243	.0439	.0074	.1807	2.141	201	.033*
Motivation: Performance Goal	.0777	.4597	.0323	.0139	.1415	2.403	201	.017*
Motivation: Achievement Goal	.0515	.5048	.0355	-.0186	.1215	1.449	201	.149
Motivation: Learning Environment Stimulation	.1446	.4970	.0350	.0756	.2135	4.134	201	.000***
Attitude: Self Awareness	.2832	.5876	.0413	.2016	.3647	6.849	201	.000***
Attitude: Learning Desire	.0381	.5426	.0382	-.0372	.1134	.998	201	.319
Attitude: Learning Method	.0337	.4314	.0304	-.0262	.0935	1.109	201	.269
Attitude: Learning Plan	.0733	.5476	.0385	-.0027	.1492	1.902	201	.059
Attitude: Learning Habit	.0832	.5623	.0396	.0051	.1612	2.102	201	.037*
Attitude: Learning Process	.0505	.5294	.0372	-.0229	.1239	1.356	201	.177

attitudes, fostering a more dynamic, engaging, and effective learning environment.

Conclusion and recommendations

Conclusions

During the COVID-19 pandemic, many classes relied heavily on digital technologies, and this course was no exception. LINE groups were used to facilitate group discussions and keep students engaged, even when in-person attendance was not feasible. Despite these challenges, students remained focused and gained valuable insights through online interactions. Given the growing importance of AI and bilingual capabilities for future national competitiveness, the integration of AI-related content into the mandatory general education curriculum was vital in equipping students with skills that align with global advancements.

The use of Google Translate to support AI-related English vocabulary and pronunciation significantly enhanced students' learning motivation and attitudes. The course not only deepened their understanding of AI but also fostered skills that are relevant to international trends.

The empirical findings confirm that the TAM remains a reliable framework for understanding technology acceptance in a multimodal interactive teaching environment. Most of the model's paths exhibit significant positive relationships, except for the link between PEOU and UA. A possible explanation for this is that both LINE and Google Translate are inherently user-friendly, making ease of use less influential than other factors. The analysis also revealed variations in technology acceptance behaviors across students from different departments, emphasizing the need for educators to consider these differences when applying new teaching methods.

The course incorporated AI-related English vocabulary quizzes and interactive teaching methods, motivating students to use Google Translate for pronunciation assistance. By integrating a PBL approach and fostering collaborative learning through LINE group discussions, students became more actively engaged with the course content. The condensed course structure allowed them to explore a broad range of knowledge, significantly enriching their learning experience.

In conclusion, the AI-focused general education course successfully enhanced students' motivation, attitudes, and understanding of AI. The combination of technology integration and dynamic teaching methods contributed to creating a positive and impactful learning environment.

Future research

This study utilizes the TAM to investigate the acceptance of AI-related tools in education. TAM is favored for its simplicity compared to the Unified Theory of Acceptance and Use of Technology (UTAUT). The choice of TAM stems from its focused scope and ease of application, which makes it suitable for exploring the mediating effects of PEOU and PU in the relationship between system characteristics and technology acceptance (Legris et al., 2003). TAM has been widely validated in numerous studies and remains one of the most commonly used models for measuring technology acceptance (Ma & Liu, 2004). In contrast, UTAUT includes additional variables such as social influence, facilitating conditions, and hedonic motivation to predict user intentions and behaviors toward technology adoption (Harnadi et al., 2022). While UTAUT offers a more comprehensive framework, TAM provides a foundational approach that effectively addresses the key variables relevant to this study.

While TAM is useful for examining PU and PEOU, along with their impact on users' attitudes and intentions, future research could benefit from applying UTAUT to explore additional constructs, such as social influence and facilitating conditions. By incorporating these additional factors, UTAUT could offer more comprehensive insights into technology acceptance within educational settings, helping to better understand the complex factors that influence user behavior.

Moreover, gamification and game-based learning are emerging technologies that educators are increasingly adopting to enhance student engagement and skill development (Emihovich, 2024). The global sales revenue from gamification is expected to reach $32 billion by 2025, while the game-based learning market is projected to be valued at $25.7 billion (O'Neill, 2022). As these methods gain traction in educational settings, future research could examine how they affect technology acceptance and learning outcomes. In terms of learning outcomes, maintaining focus and immersion can significantly enhance a student's learning experience (Dahalan et al., 2024). For example, Green and Bavelier (2003) find that video game players improved their visual attention, while Anderson and Bavelier (2011) show that fast-paced action games enhanced perception, attention, and cognitive processes. Similarly, Karle et al. (2010) observe that computer game players had significantly faster reaction times on complex perceptual tasks. Understanding the role of gamification in technology acceptance could provide valuable insights for future educational technologies and instructional strategies.

Acknowledgement

The author would like to thank the Ministry of Education, Taiwan, R.O.C. for its partial financial support to this study, under Project Number PGE1110076.

Appendix 1. Question Items of TAM

Variable	Item
PU (Perceived Usefulness)	• PU1: I believe using AI-powered Google Translate enhances my English vocabulary. • PU2: I believe using AI-powered Google Translate helps me understand my English vocabulary deficiencies. • PU3: I believe using AI-powered Google Translate assists me in strengthening my English vocabulary.
PEOU (Perceived Ease of Use)	• PEOU1: I think AI-powered Google Translate is easy to use. • PEOU2: I think the operational process of AI-powered Google Translate is simple. • PEOU3: I think the interface menu of AI-powered Google Translate is clear.
UA (Attitude Toward Use)	• UA1: I believe I should use AI-powered Google Translate to help improve my English vocabulary. • UA2: I think AI-powered Google Translate is a good tool for enhancing my English vocabulary. • UA3: I think using AI-powered Google Translate is a good method for addressing my English vocabulary deficiencies.
UI (Usage Intention)	• UI1: I am willing to regularly use AI-powered Google Translate to help improve my English vocabulary. • UI2: I am willing to recommend my classmates use AI-powered Google Translate to help with their English vocabulary. • UI3: I am willing to recommend my friends and family use AI-powered Google Translate to help with their English vocabulary.

References

Akhdinirwanto, R. W., Agustini, R., & Jatmiko, B. (2020). Problem-based learning with argumentation as a hypothetical model to increase the critical thinking skills for junior high school students. *Journal Pendidikan IPA Indonesia, 9*(3), 340–350. https://doi.org/10.15294/jpii.v9i3.19282

Aldahdouh, T. Z., Nokelainen, P., & Korhonen, V. (2020). Technology and social media usage in higher education: The influence of individual innovativeness. *Sage Open, 10* (1), Article 2158244019899441. https://doi.org/10.1177/2158244019899441

Al-Qaysi, N., Granić, A., Al-Emran, M., Ramayah, T., Garces, E., & Daim, T. U. (2023). Social media adoption in education: A systematic review of disciplines, applications, and influential factors. *Technology in Society*. , Article 102249. https://doi.org/10.1016/j.techsoc.2023.102249

Anderson, A. F., & Bavelier, D. (2011). Action game play as a tool to enhance perception, attention and cognition. In S. Tobias, & J. D. Fletcher (Eds.), *Computer games and instruction* (pp. 307–330). Charllotte, NC: Information Age.

Betihavas, V., Bridgman, H., Kornhaber, R., & Cross, M. (2016). The evidence for flipping out: A systematic review of the flipped classroom in nursing education. *Nurse Education Today, 38*, 15–21. https://doi.org/10.1016/j.nedt.2015.12.010

Blankesteijn, M. L. M., Houtkamp, J., & Bossink, B. (2024). Towards transformative experiential learning in science-and technology-based entrepreneurship education for sustainable technological innovation. *Journal of Innovation & Knowledge, 9*(3), Article 100544. https://doi.org/10.1016/j.jik.2024.100544

Callaghan, G., & Fribbance, I. (2016). The use of Facebook to build a community for distance learning students: A case study from the Open University. *Open Learning: The Journal of Open, Distance and e-Learning, 31*(3), 260–272. https://doi.org/10.1080/02680513.2016.1229176

Dahalan, F., Alias, N., & Shaharom, M. S. N. (2024). Gamification and game based learning for vocational education and training: A systematic literature review. *Education and Information Technologies, 29*(2), 1279–1317. https://doi.org/10.1007/s10639-022-11548-w

D'Alessio, F. A., Avolio, B. E., & Charles, V. (2019). Studying the impact of critical thinking on the academic performance of executive MBA students. *Thinking Skills and Creativity, 31*, 275–283. https://doi.org/10.1016/j.tsc.2019.02.002

Davidovitch, N., & Belichenko, M. (2018). Facebook tools and digital learning achievements in higher education. *Journal of Education and e-Learning Research, 5*(1), 8–14. https://doi.org/10.20448/journal.509.2018.51.8.14

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1989). User acceptance of computer technology: A comparison of two theoretical models. *Management Science, 35*(8), 982–1003. https://doi.org/10.1287/mnsc.35.8.982

de Moraes Abrahão, V., Vaquero-Diego, M., & Currás Móstoles, R. (2024). University social responsibility: The role of teachers. *Journal of Innovation & Knowledge, 9*(1), Article 100464. https://doi.org/10.1016/j.jik.2024.100464

Emihovich, B. (2024). Game-based learning and systems thinking: An innovative instructional approach for the 21st century. *TechTrends, 68*(1), 174–185. https://doi.org/10.1007/s11528-023-00915-0

Fong, C. J., Kim, Y., Davis, C. W., Hoang, T., & Kim, Y. W. (2017). A meta-analysis on critical thinking and community college student achievement. *Thinking Skills and Creativity, 26*, 71–83. https://doi.org/10.1016/j.tsc.2017.06.002

Foo, C. C., Cheung, B., & Chu, K. M. (2021). A comparative study regarding distance learning and the conventional face-to-face approach conducted problem-based learning tutorial during the COVID-19 pandemic. *BMC Medical Education, 21*, 1–6. https://doi.org/10.1186/s12909-021-02575-1

Giannikas, C. (2020). Facebook in tertiary education: The impact of social media in e-learning. *Journal of University Teaching and Learning Practice, 17*(1), 3. https://doi.org/10.53761/1.17.1.3

Green, C. S., & Bavelier, D. (2003). Action video game modifies visual selective attention. *Nature, 423*, 534–537. https://doi.org/10.1038/nature01647

Harnadi, B., Prasetya, F. H., & Widiantoro, A. D. (2022). Understanding Behavioral Intention to Use Social Media Technology: Two Comparing Model, TAM and UTAUT. In *2022 6th International Conference on Information Technology (InCIT)* (pp. 352–357). IEEE. https://doi.org/10.1109/InCIT56086.2022.10067645.

Hidayati, N., Zubaidah, S., & Amnah, S. (2022). The PBL vs. digital mind maps integrated PBL: Choosing between the two with a view to enhance learners' critical thinking. *Participatory Educational Research, 9*(3), 330–343. https://doi.org/10.17275/per.22.69.9.3

Huang, D.-H., & Chueh, H.-E. (2021). Chatbot usage intention analysis: Veterinary consultation. *Journal of Innovation & Knowledge, 6*(3), 135–144. https://doi.org/10.1016/j.jik.2020.09.002

Jafarigohar, M., Hemmati, F., Rouhi, A., & Divsar, H. (2016). Instructors' attitudes towards the reflection of critical thinking in course syllabi: Evidence from an expanding circle. *Theory and Practice in Language Studies, 6*(1), 59. https://doi.org/10.17507/tpls.0601.08

Johnson, D. W., & Johnson, R. T. (2018). Cooperative learning: The foundation for active learning. In S. M. Brito (Ed.), *Active learning - Beyond the future* (pp. 59–70). London, UK: Intech Open. https://doi.org/10.5772/intechopen.81086.

Karle, J. W., Watter, S., & Shedden, J. M. (2010). Task switching in video game players: Benefits of selective attention but resistance to proactive interference. *Acta Psychologica, 134*, 70–78. https://doi.org/10.1016/j.actpsy.2009.12.007

Kwangsawad, A., & Jattamart, A. (2022). Overcoming customer innovation resistance to the sustainable adoption of chatbot services: A community-enterprise perspective in Thailand. *Journal of Innovation & Knowledge, 7*(3), 100211. https://doi.org/10.1016/j.jik.2022.100211

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*(3), 191–204. https://doi.org/10.1016/S0378-7206(01)00143-4

Li, L. (2023). Critical thinking from the ground up: Teachers' conceptions and practice in EFL classrooms. *Teachers and Teaching, 29*(6), 571–593. https://doi.org/10.1080/13540602.2023.2191182

Ma, Q., & Liu, L. (2004). The technology acceptance model: A meta-analysis of empirical findings. *Journal of Organizational and End User Computing (JOEUC), 16*(1), 59–72. https://doi.org/10.4018/joeuc.2004010104

Moghavvemi, S., Paramanathan, T., Rahin, N., & Sharabati, M. (2017). Student's perceptions towards using e-learning via Facebook. *Behaviour & Information Technology, 36*(10), 1081–1100. https://doi.org/10.1080/0144929X.2017.1347201

Moorthy, K., T'ing, L. C., Wei, K. M., Mei, P. T. Z., Yee, C. Y., Wern, K. L. J., & Xin, Y. M. (2019). Is Facebook useful for learning? A study in private universities in Malaysia. *Computers & Education, 130*, 94–104. https://doi.org/10.1016/j.compedu.2018.12.002

O'Neill, S. (2022). Gamification in marketing: Stats and trends for 2023. LXA, learning experience alliance. https://www.martechalliance.com/stories/gamification-in-marketing-stats-and-trends-for-2022.

Saiful, A. M. I. N., Utaya, S., Bachri, S., Sumarmi, S., & Susilo, S. (2020). Effect of problem based learning on critical thinking skill and environmental attitude. *Journal for the Education of Gifted Young Scientists, 8*(2), 743–755. https://doi.org/10.17478/jegys.650344

Sharan, Y., & Sharan, S. (2021). Design for change: A teacher education project for cooperative learning and group investigation in Israel. In N. Davidson (Ed.), *Pioneering perspectives in cooperative learning: Theory, research, and classroom practice for diverse approaches to cl* (pp. 165–182). Routledge.

Sheeran, N., & Cummings, D. (2018). An examination of the relationship between Facebook groups attached to university courses and student engagement. *Higher Education, 76*(6), 937–955. https://doi.org/10.1007/s10734-018-0253-2

Shek, D. T. L., Yuen-Tsang, A. W. K., & Ng, E. C. W. (2017). USR network: A platform to promote university social responsibility. In D. T. L. Shek, & R. M. Hollister (Eds.), *University social responsibility and quality of life: A global survey of concepts and experiences* (pp. 11–21). Singapore: Springer. https://doi.org/10.1007/978-981-10-3877-8_2.

Slavin, R. E. (1987). Cooperative learning and the cooperative school. *Educational Leadership, 45*(3), 7–13.

Song, B. (2024). Multimodal interactive classroom teaching strategies based on social network analysis. *International Journal of Networking and Virtual Organisations, 30*(1), 70–81. https://doi.org/10.1504/IJNVO.2024.136777

Taghizadeh, M., & Hajhosseini, F. (2021). Investigating a blended learning environment: Contribution of attitude, interaction, and quality of teaching to satisfaction of graduate students of TEFL. *The Asia-Pacific Education Researcher, 30*(5), 459–469. https://doi.org/10.1007/s40299-020-00531-z

Tan, P. J. B., & Hsu, M. H. (2018). Designing a system for English evaluation and teaching devices: A PZB and TAM model analysis. *Eurasia Journal of Mathematics,* *Science and Technology Education, 14*(6), 2107–2119. https://doi.org/10.29333/ejmste/86467

Wu, Y. J., & Chen, J. C. (2021). Stimulating innovation with an innovative curriculum: A curriculum design for a course on new product development. *The International Journal of Management Education, 19*(3), Article 100561. https://doi.org/10.1016/j.ijme.2021.100561

Yao, Y., Wang, P., Jiang, Y. J., Li, Q., & Li, Y. (2022). Innovative online learning strategies for the successful construction of student self-awareness during the COVID-19 pandemic: Merging TAM with TPB. *Journal of Innovation & Knowledge, 7*(4), Article 100252. https://doi.org/10.1016/j.jik.2022.100252