ISSN 1799-2591 (print); ISSN 2053-0692 (online)
Theory and Practice in Language Studies, Vol. 16, No. 9, pp. 3111-3121, September 2026
DOI: https://doi.org/10.17507/tpls.1609.18

Digital Scaffolding in Action: AI-Supported Cover Letter Writing Among Thai EFL Business Students

Pimpisa Chanted
Faculty of Management Sciences, Kasetsart University, Sriracha Campus, Chonburi, Thailand

***Abstract*—Generative AI is increasingly used in EFL writing classrooms, but there is little research on high-stakes professional genres such as cover letters, particularly in the context of Thai EFL business students. This mixed-methods study assessed the quality of AI-assisted cover letters and students' acceptance of AI writing support. Fifty-five Thai EFL business undergraduates produced AI-assisted cover letters, completed a Technology Acceptance Model (TAM) questionnaire together with measures of cultural dimensions, and 13 students participated in semi-structured interviews. Overall writing quality was mixed (M = 12.78/18), with the strongest performance in language accuracy (M = 4.69/6) and organization and coherence (M = 4.44/6) than in adhering to genre and format expectations (M = 3.65/6). Students showed strong acceptance of AI support (TAM composite M = 4.10/5). Perceived usefulness was correlated with organization and coherence (Spearman's rho = .319, p = .018), perceived ease of use was correlated with organization and coherence (Spearman's rho = .349, p = .009), and the overall TAM score was correlated with organization and coherence (Spearman's rho = .278, p = .040). Power distance showed moderate-to-strong correlations with acceptance measures (rho = .474–.652, p < .001). Data from the interviews revealed that students were using AI for task planning, language polishing, and proofreading, and they also expressed concerns about voice authenticity, dependence on AI, and output quality. These findings suggest that AI assistance can support professional writing development when instruction emphasizes genre knowledge and verification strategies**.

***Index Terms*—AI writing assistance, cover letter writing, scaffolding, technology acceptance model, Thai EFL undergraduates**

I. Introduction

A. Background and Rationale

English proficiency is increasingly essential for business students who must produce high-stakes professional genres such as cover letters. The hiring process uses cover letters as its initial evaluation method, demanding correct language use, effective writing structure, suitable professional demeanor, and authentic presentation of work experience. The research on genres shows that workplace texts become effective through their ability to fulfill requirements of their discourse community while performing established rhetorical functions (Swales, 1990). Thai EFL students face increasing writing difficulties because they need to learn professional document writing and their cultural background influences their official self-presentation and face management techniques (Buripakdi & An, 2024; Limna & Shaengchart, 2025).

The public now has access to generative AI tools including ChatGPT which people use to get help with their writing tasks. AI systems function as digital scaffolding tools which offer learners instant access to relevant examples and feedback and prompts which assist their text planning and drafting and revision processes. The educational value of AI depends on student interactions with the tool during writing tasks and their assessment and modification of AI-generated suggestions. Users maintain their technology usage based on their evaluation of tool performance and their ability to operate tools and their overall perception of the tool (Davis, 1989; Venkatesh & Davis, 2000). The way people view and use technology depends on their cultural background, as their cultural values about power distribution, group unity, and comfort with the unknown shape their behavior.

B. Research Gaps

Despite the increasing body of literature on AI-assisted writing, there are empirical gaps in high-stakes professional genres, the composing process within the learner-AI dyad, and cultural dimensions affecting writing quality and acceptance, with special reference to Thai EFL learners, as elaborated in the literature review (Section II-F).

C. Research Objectives and Questions

Objectives

1. To examine how Thai business students use AI as digital scaffolding across planning, drafting, revising, and verifying their cover-letter writing.
2. To investigate students' perceptions and attitudes toward AI writing support in terms of perceived usefulness, perceived ease of use, and overall attitudes/challenges.

3. To examine the relationships between Thai cultural dimensions (e.g., power distance, collectivism, uncertainty avoidance) and students' acceptance and use of AI in professional writing contexts.

Research Questions

RQ1. How do Thai business students use AI as digital scaffolding when writing cover letters?

RQ2. What are the usefulness, usability, and difficulties of AI writing assistance as perceived and experienced by students?

RQ3. How do Thai cultural dimensions relate to students' acceptance and use of AI in cover-letter writing?

To answer these questions, the study employed a mixed-methods design combining rubric-based assessment of cover-letter drafts with survey and interview data on learners' AI use and perceptions.

D. Conceptual Framework

Sociocultural theory frames AI as a mediational tool that extends learners' capacity within their ZPD (Vygotsky, 1978), supporting iterative prompting, drafting, and revision. The second point shows how cover letters function as professional documents that need writers to follow established writing rules and choose appropriate language to reach their target audience (Swales, 1990). The model of AI adoption by learners depends on TAM constructs, which include perceived usefulness and perceived ease of use and attitudes that affect how deeply and for how long learners will use AI (Davis, 1989; Venkatesh & Davis, 2000). The way learners understand AI feedback and their choice to use it will be influenced by their Thai cultural background which includes power distance and collectivism and uncertainty avoidance dimensions. The conceptual framework is shown in Figure 1.

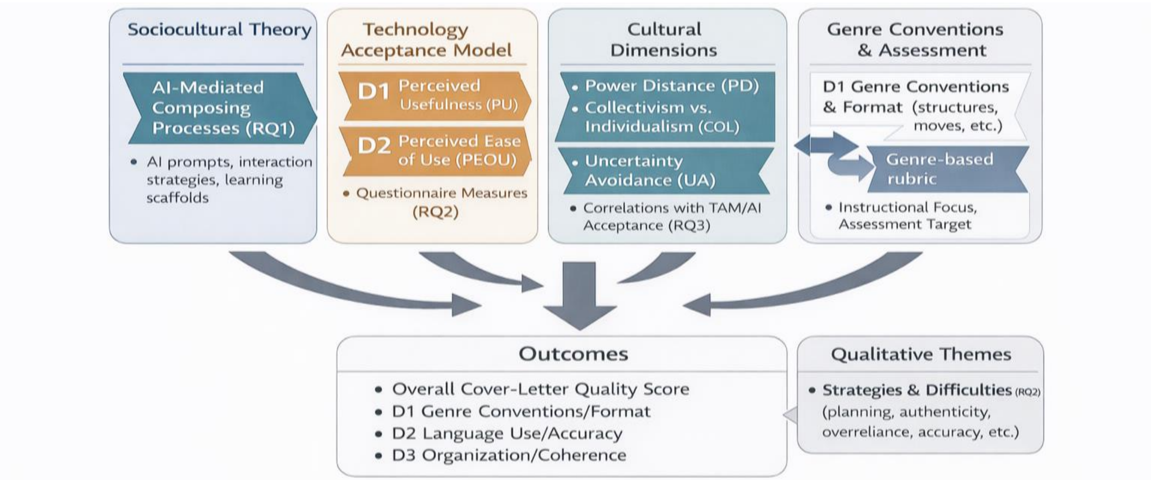

Figure 1. Conceptual Framework for AI-Assisted Cover-Letter Writing: (RQ1) Learners' AI-Mediated Composing Processes, (RQ2) Perceived Usefulness, Ease of Use, Attitudes, and Difficulties, and (RQ3) Cultural Dimensions Related to AI Acceptance and Use, With Outcomes Evaluated Through Rubric-Based Cover-Letter Quality (D1–D3)

E. Contribution & Organization of Paper

The contribution of the study appears in three specific areas: (a) Study of cover letters as professional writing texts (b) Combination of three assessment tools within a mixed method framework that includes rubric-based writing assessments, student responses to written assignments, and interview responses. (c) Situating the study within a research framework that acknowledges the influence of culture on technology use within a Thai EFL learning ecosystem. The study uncovers an AI mediation effect between instruction and learning that only manifests when students engage with technology in a strategic, reflective, and responsible manner. The sections of the paper are: II. Theory and Prior Research, III. Methods, IV. Results, V. Discussion, and VI. Conclusion.

II. LITERATURE REVIEW

A. Cover Letters as a Genre of Professional Writing

Employees in the workplace need to write cover letters that show their work qualifications and professional skills through detailed information within strict word count boundaries that follow established rhetorical structures. The study of genres shows that writers need to understand how their messages will function in their audience's setting because this understanding leads to improved writing outcomes than their command of correct language (Swales, 1990). The process of writing cover letters demands authors to start with their message purpose, followed by demonstrating their qualifications for the position and showing their relevant skills, before ending with a suitable request for action which needs to be achieved through direct and respectful language.

EFL writers face difficulties when creating cover letters because they need to understand unknown genre conventions while they need to handle three essential tasks which include selecting content and organizing it and maintaining language precision. The writing process according to Flower and Hayes (1981), follows a cognitive model which divides writing into three continuous stages that start with planning then move to translation and finish with revision. Writers who have restricted language abilities need to focus on their sentence structure which reduces their ability to adjust their message for their audience and create a unified overall structure.

B. Scaffolding and Writing Development in a Sociocultural Perspective

The process of supporting new writers involves scaffolding, which helps them reach their zone of proximal development (ZPD) (Vygotsky, 1978) through brief instructor help that lets students achieve tasks they cannot do alone before they learn to perform them independently. The research on problem-solving tutoring through classic studies shows that tutors need to give assistance based on student needs while they should decrease their help when students show increasing mastery (Wood et al., 1976). Teachers who use scaffolding to teach writing need to provide students with model texts and guided planning prompts and feedback cycles and structured revision activities. The process of scaffolding becomes essential for professional writing because new writers cannot perform genre-specific moves and pragmatic tone and they face challenges when trying to understand workplace expectations from their brief experience.

AI writing assistants in digital environments provide scaffolding support through their accessible prompts and examples and a feedback system which enables students to identify their weaknesses and practice their language skills and improve their organizational abilities. The educational value of tool-based support depends on the particular methods that instructors choose to use. The scaffolding system which helps students develop metacognitive abilities through planning and monitoring and revision works differently from the support that takes over their composing tasks.

C. AI-Mediated Writing Support: From AWE to LLMs

AI can help with writing, ranging from automated writing evaluation (AWE) and grammar checking to generative tools that can draft extended texts in context. With LLMs like ChatGPT, writers can request explanations, rewordings, variations in vocabulary and suggestions for the organization of their work. The dialogic nature of these instruments invites a dialogic approach to process writing instruction.

Recent empirical studies in the EFL context typically identify benefits for brainstorming, outlining, and language support. For example, a mixed-methods study on Thai and Vietnamese EFL learners reported overall positive experiences with ChatGPT for L2 writing. Learners reported using the tool to generate ideas, structure content, clarify concepts, and revise drafts (Meniado et al., 2024). In a case study on learning writing registers, participants reported it was beneficial for learning formal register knowledge, but they also noted task-dependent limitations (Özçelik & Ekşi, 2024). The importance of how learners engage with tools in studies like this one emphasize that the tool should be viewed as a learning scaffold, not a substitution.

Within Theory and Practice in Language Studies—Nguyen (2026) showed that Vietnamese EFL undergraduates reported finding ChatGPT most useful for generating ideas for their writing and for enhancing the coherence, cohesion, and vocabulary of drafts, as well as for checking grammar. Nonetheless, they raised concerns about the potential for cheating, dependence on the tool, and the accuracy of responses.

Generative AI technologies also pose risks that need to be addressed in a suitable pedagogical framework. Students and teachers have expressed worries about overdependence, errors or "hallucinated" content, and loss of authorial voice, etc. A mixed-methods study on students' perceptions and interview responses about the use of ChatGPT for writing support reported that the eagerness for these technologies' speed and readability is tempered by uncertainty about their reliability and academic integrity implications (Alharbi & Al-Ahdal, 2025). For high-stakes professional writing tasks, however, some of these issues may be particularly problematic due to the genre-specific demands of credible personalization and the need to maintain a professional identity.

D. Technology Acceptance and Culturally Situated Perceptions of AI Support

The Technology Acceptance Model (TAM) states that perceived usefulness and perceived ease of use have a positive influence on users' attitude towards using a technology and on their behavioral intention to use said technology (Davis, 1989). In the education literature, TAM has been widely applied to explain learners' acceptance of learning technologies, particularly those designed to support writing. Extensions of TAM and unified acceptance models also suggest that social and facilitating conditions influence the acceptance of new technology (Venkatesh & Davis, 2000; Venkatesh et al., 2003).

However, culturally situated orientations may also moderate the perception of AI writing support. The reliance on individual agency versus external support may be perceived differently as a function of the learner's cultural orientation. Thus, for instance, collectivists may pay more attention to how much using a writing assistant satisfies collectivist-defined expectations for quality, whereas those exhibiting higher power distance may show more appreciation for authoritative AI-generated instructions and may perceive "correct" outputs differently. The uncertainty avoidance disposition may again relate to favorable views for tools that reduce ambiguity and provide clear guidance, while at the same time instilling doubts regarding the usefulness of AI-generated content. Incorporating dimensions of culture into TAM provides a richer explanation for learners' context-dependent acceptance or rejection of AI-based writing support.

E. Thai EFL Context and Local Evidence on AI-Assisted Writing

Thai EFL university students commonly report difficulties with English writing, weak lexical resources, grammatical accuracy, and text-level organization, all combined with limited opportunities for individualized teacher feedback. The local literature on AI-supported writing for EFL learning is rapidly developing and has implications for this study. For instance, Thai university students have recently made public their views on generative AI, stating that it is very helpful for idea generation, text organization, and language correction but that it must be treated as a thinking partner rather than a source of uncritically accepted text (Limna & Shaengchart, 2025) Doctoral students at a Thai university have articulated some of the same dilemmas about the responsible use of such technologies and their academic integrity implications (Buripakdi & An, 2024).

The Thai-context studies written about earlier generations of AI-supported writing tools have similar benefits and limitations. The literature on grammar-checkers, for instance, has confirmed that the suggestions made by such programs vary widely in accuracy and often substitute one error for another, reinforcing rather than undermining the need for informed user judgment rather than blind acceptance (Sanderson & Stephens, 2023). Taken together, the local scholarship suggests that learner perceptions (usefulness, ease of use, and attitudes) toward AI are associated with concerns about trustworthiness, ethics, and text voice.

F. Summary and Research Gap

Formerly-established knowledge of professional genres like cover letters states that they (a) require rhetorical competence and use linguistically correct language (Swales, 1990), (b) develop genre-aware writing competence with scaffolding and feedback cycles (Wood et al., 1976), and (c) LLM-based tools can support writing but present risks of dependence, text integrity, and author voice (Alharbi & Al-Ahdal, 2025; Meniado et al., 2024). As a sociocultural theory, AI can be viewed as a mediational tool that supports the development of learners' self-regulation within the zone of proximal development during composing (Vygotsky, 1978). Acceptance-based models explain why learners adopt tools (Davis, 1989; Venkatesh et al., 2003), but few studies connect acceptance constructs to culturally situated perceptions and independent ratings of professional writing quality. Yet evidence from the Thai context regarding generative AI and writing is just beginning to emerge (Buripakdi & An, 2024; Limna & Shaengchart, 2025), but its connections to genre-based assessment of workplace writing have yet to be established. Addressing these gaps, the present study connects rubric-based cover-letter scores to perceptions (usefulness, ease of use, attitude) and cultural dimensions, and triangulates these quantitative findings with themes from interview data that describe how learners use AI in the writing process.

III. Method

A. Research Design

The research employed an explanatory sequential mixed methods design (Creswell & Plano Clark, 2018). The first phase consisted of the collection and analysis of quantitative data which would enable the identification of patterns in the quality of the AI-generated cover letters and levels of technology acceptance and cultural orientations of the students. The second phase consisted of the collection of qualitative interviews which would provide an explanatory level of understanding of the students' AI-based composing processes, perceptions and experienced difficulties. The integration of the two approaches occurred via a joint display of the findings from the two approaches, consisting of the key results from the quantitative analysis and relevant explanatory qualitative themes, yielding meta-inferences.

B. Context and Participants

The study was carried out in an English for Professional purposes class at a Thai public university where business undergrads write for the work environment. The participants in the quantitative phase consisted of 55 Thai EFL business undergraduates. All participants provided informed consent and completed the writing task and online questionnaire.

Qualitative sampling of 13 participants was conducted using purposive sampling to represent a range of writing skills and acceptance of AI, with sampling continuing until thematic saturation in this small setting (Guest et al., 2006).

C. Instruments and Measures

Three data sources were used: (1) AI-based artifacts from cover letters that were evaluated using an analytic rubric, (2) an online questionnaire, and (3) semi-structured interviews. The measures were validated by experts and slightly modified for use.

1) Writing of Cover Letter and Rubric

Participation required writing one English cover letter (200–300 words) for a marketing assistant position in response to a job advertisement read in class.

2) Online Questionnaire

An online questionnaire (in Thai) was administered to collect self-reports about (a) demographics, (b) AI usage, (c) technology acceptance, and (d) cultural orientations related to AI usage in writing. Technology acceptance was measured with 12 questions to assess Perceived Usefulness (PU; items 12–15), Perceived Ease of Use (PEOU; items 16–19), and Attitudes toward AI (ATT; items 20–23) on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The cultural dimensions were measured at the individual level using contextually framed questions following Hofstede's theory of cultural dimensions (Hofstede, 2001; Yoo et al., 2011). Three dimensions were measured: Collectivism (items

24–26), Power Distance (items 27–29), and Uncertainty Avoidance (items 30–32). Since these were contextually adapted (i.e., not translated from a known measure), caution should be applied when interpreting reliability. Content validity was reviewed by experts, and internal consistency reliability was assessed using Cronbach's alpha.

3) Semi-Structured Interviews

The interviews were semi-structured and an interview guide was developed to facilitate the purpose of the study and the research question (RQ1) "Questions targeted (RQ1) students' AI-assisted composing process (e.g., when and how they used AI, how they prompted and revised), (RQ2) perceived benefits, challenges, and ease of use, and (RQ3) cultural and ethical considerations shaping AI use".

Interviews were conducted in the Thai language, recorded with permission and took 30–45 minutes. Transcripts were generated in Thai.

D. Data Collection Procedure

Data collection took place in three stages. (1) Participants completed and returned the AI-assisted cover-letter task. (2) Participants completed an online questionnaire. (3) Following preliminary quantitative analysis, participants were selected via purposeful sampling techniques for an interview to gain additional contextualization of their quantitative responses.

E. Data Analysis

1) Quantitative Analysis

Rubric scores were summarized (means and standard deviations) by dimension (D1-D3) and overall score. Composite means were calculated for each questionnaire construct. Reliability was assessed by Cronbach's alpha. Due to the ordinal, bounded nature of Likert items, relationships between constructions were assessed with Spearman's rank-order correlation (ρ). p-values were set at $< .05$.

2) Qualitative Analysis and Trustworthiness

The interview data were analyzed using thematic analysis (Braun & Clarke, 2006). A preliminary codebook was developed deductively from the research questions and inductively refined as patterns emerged in the data. The coding was done iteratively with repeated scanning of the transcripts to ensure that codes were used consistently. Themes were tested for internal coherence and distinctiveness across the dataset.

The trustworthiness of qualitative coding by a single researcher was addressed through maintaining an audit trail of the analytic decisions made at various stages of analysis, including the development of themes, and using representative quotes that reflect each of the themes. Additionally, English translations of quoted excerpts were compared against the original Thai transcripts to conceptualize correctly. Finally, deviant-case analysis was used as needed to avoid over-explaining.

3) Integration

Quantitative and qualitative data were combined in a joint presentation of statistical findings (e.g., quality profiles of writing, acceptance measures) and interpretive themes (e.g., strategies for using AI, value and challenges associated with AI) in a meta-inference concerning the role of AI acceptance and culture-oriented AI use strategies in determining the impact of AI-supported writing in this specific context.

F. Ethical Considerations

Participation in the study was voluntary. Informed consent was secured before data collection. Data were anonymized using participant codes, securely stored, and used solely for research purposes. Participants were informed that they could withdraw from the study at any time without negative consequences.

IV. RESULTS

Quantitative, Qualitative, and Integrated Findings

A. Quantitative Findings

Reliability of rubric scoring

Reliability of raters was assessed in a subset of the data rated twice (n = 10) using the intraclass correlation coefficient (ICC) for a two-way random-effects model (absolute agreement) (Shrout & Fleiss, 1979). Interpretation followed common guidelines for ICC magnitudes (Koo & Li, 2016). Coefficients were moderate to high across dimensions, supporting the reliability of the rubric scoring. The ICC results are reported in Table 1.

TABLE 1
INTER-RATER RELIABILITY OF THE COVER LETTER RATING SCALE (ICC, N = 10)

Dimension	ICC (2,1)	ICC (2,2)	Interpretation
D1 - Genre conventions and format	0.894	0.944	Good-Excellent
D2 - Language use and accuracy	0.757	0.862	Good
D3 - Organization and coherence	0.690	0.816	Moderate-Good
Total score	0.838	0.912	Good-Excellent

Note. ICC (2,1) = single-measure reliability; ICC (2,2) = reliability of the mean of two raters.

Cover letter writing performance

As shown in Table 2, students' cover letter scores (n = 55) on the three rubric dimensions and total score (0–18) indicated higher performance for Language Use and Accuracy (D2; M = 4.69, SD = 0.74) and Organization and Coherence (D3; M = 4.44, SD = 0.74) than for Genre Conventions and Format (D1; M = 3.65, SD = 1.64), suggesting comparatively weaker performance in genre-related features. The wide range of values for D1 (Min = 0, Max = 6) demonstrates that a small number of letters were not conforming to the genre structure of cover letters and this was the reason for D1 having the highest SD (1.64) compared to D2 and D3. Total scores averaged 12.78 (SD = 2.03), suggesting overall satisfactory to good performance across the sample.

TABLE 2
DESCRIPTIVE STATISTICS OF COVER LETTER SCORES (N = 55)

Dimension	M	SD	Min	Max
D1 - Genre conventions and format	3.65	1.64	0	6
D2 - Language use and accuracy	4.69	0.74	3	6
D3 - Organization and coherence	4.44	0.74	3	6
Total score (0-18)	12.78	2.03	8	18

Note. Each dimension has a score between 0 and 6; the total score has a range of 0 to 18.
For interpretation only, the scores on the 0–18 score scale were grouped with scoring rubrics (Excellent: 16–18, Good: 13–15, Satisfactory: 10–12, Poor: 0–9). The rated percents are: 10.91% Excellent; 54.55% Good; 30.91% Satisfactory and 3.64% Poor.

Questionnaire dimensions: AI acceptance and cultural dimensions

Students reported positive attitudes towards writing with AI. Internal consistency estimates for all scales were acceptable to excellent. Descriptive statistics and internal consistency estimates are presented in Table 3.

TABLE 3
DESCRIPTIVE STATISTICS AND INTERNAL RELIABILITY OF QUESTIONNAIRE SCALES (N = 55)

Scale	M	SD	Cronbach's alpha
Perceived usefulness (PU)	4.30	0.57	0.898
Perceived ease of use (PEOU)	4.03	0.68	0.786
Attitude toward AI (ATT)	3.98	0.71	0.915
TAM composite	4.10	0.55	—
Collectivism (COL)	3.99	0.82	0.854
Power distance (PD)	3.89	0.70	0.725
Uncertainty avoidance (UA)	3.96	0.74	0.710

Note. All items were rated on a 5-point scale. Alpha is not reported for the TAM composite (mean of subscales).

Associations between perceptions and writing performance

Spearman correlations showed small-to-medium positive correlations between Perceived Usefulness, Perceived Ease of Use, and Organization and Coherence (D3) (PU–D3: $\rho = .319$, $p = .018$; PEOU–D3: $\rho = .349$, $p = .009$). The TAM composite score was also positively correlated with D3 ($\rho = .278$, $p = .040$). Correlations with Genre Conventions (D1), Language Use and Accuracy (D2), and overall writing scores were not statistically significant (ps > .05). Pearson correlations showed a largely consistent pattern: PEOU–D3 ($r = .307$, $p = .022$) and TAM–D3 ($r = .283$, $p = .036$) remained significant, whereas PU–D3 did not reach significance under Pearson ($r = .249$, $p = .067$), suggesting the PU–D3 association should be interpreted with some caution (see Appendix B). Full correlations are reported in Table 4.

Cultural dimensions and technology acceptance

Power distance showed in Table 4 the strongest positive associations with all technology acceptance measures in the Spearman correlations.

TABLE 4
SPEARMAN CORRELATIONS (RHO) AMONG KEY STUDY VARIABLES (N = 55)

Panel A. AI acceptance (TAM) and writing scores				
Construct	**D1**	**D2**	**D3**	**Total**
PU	-0.134 (p = .328)	0.058 (p = .672)	0.319* (p = .018)	-0.016 (p = .908)
PEOU	-0.179 (p = .192)	0.183 (p = .181)	0.349** (p = .009)	0.026 (p = .853)
ATT	-0.148 (p = .280)	0.038 (p = .784)	0.186 (p = .175)	-0.126 (p = .361)
TAM	-0.203 (p = .137)	0.081 (p = .555)	0.278* (p = .040)	-0.089 (p = .520)
Panel B. Cultural dimensions and AI acceptance (TAM)				
Dimension	**PU**	**PEOU**	**ATT**	**TAM**
COL	0.498*** (p < .001)	0.211 (p = .123)	0.488*** (p < .001)	0.435*** (p < .001)
PD	0.530*** (p < .001)	0.474*** (p < .001)	0.652*** (p < .001)	0.638*** (p < .001)
UA	0.332* (p = .013)	0.070 (p = .613)	0.284* (p = .036)	0.248 (p = .068)

Note. Values are rho with p-values in parentheses. * p < .05, ** p < .01, *** p < .001.

B. Qualitative Findings

The qualitative analysis was based on the students' use of AI in the creation of their cover letters, specifically: what did the students base their decision to use a certain tool on (and if so), how did they verify their results, and finally, what ethical concern was incorporated? The researcher extracted six themes from the 13 students (S01–S13). Representative excerpts illustrating each theme are provided in Appendix A.

Theme 1. Iterative workflow and task scaffolding

The students described a recursive process in response to the chain of prompts and revisions (revising being clearly based on both the job ad and instructor expectations). The way students thought about what the AI was a scaffold for--not replacement was in generating and incorporating structure and ideas.

> *S03: "First, I see what the job required from the teacher… then I see what I had to offer… and then I made a prompt from all of that. After that, I translated and edited it, and I kept prompting until it was what I needed."*
>
> *S10: "I first saw what the teacher had to show me in terms of structure. Then, I fed that to AI and asked it to break it down for me into a structure for a cover letter. Then, I wrote along that structure, making it my own and asking ChatGPT for feedback on structure and language."*
>
> *S07: "I first looked at what the teacher provided and took notes. Then, I asked AI how to do it and followed its prompts, making it my own."*
>
> *S04: "I first give AI a role… like an HR person that looks at my resume and cover letter… then I tell AI what the position is, what skills are required, and whether or not my skills align with what the teacher asked."*

Theme 2. Lexico-grammatical support and register control

AI proved useful for grammar checking, suggested vocabulary and helped to achieve a more professional form. Yet, they also calibrated formality relative to their (e.g., 2nd year) profile and a plausible work scenario.

> *S03: "Mostly I use it to check if things are spelled correctly—whether the tense is wrong or if it looks weird—more than using it to do all my writing."*
>
> *S04: "If it feels too formal or uses words that don't fit me, I change the wording—because it's not really for me."*
>
> *S05: "At first, I used AI to translate the assignment prompt—what the teacher wanted me to focus on—then asked AI to help me draft the letter."*
>
> *S07: "It helped me see what I did wrong… sometimes even capitalization. I also used it to check for errors; make sure it was right and then revised it."*

Theme 3. Human agency and voice preservation

Participants observed that AI-generated text typically exhibits an unnatural, 'not like me' quality which needs to be fixed by human writers before it is usable. Voice authenticity was operationalized as rewriting AI output to sound more natural—modifying sentence structure, word choice, and tone to align with the writer's intended meaning.

> *S08 [context excerpt]: "It doesn't really sound like how humans talk… I made the trust level pretty high, so I always try to fix it first. Otherwise, I say: 'This is a human who does not understand the answer — once again please correct it.'"*
>
> *S04: "If it doesn't feel right, I change the words — some are too hard, some are too proper."*
>
> *S13 [workflow excerpt]: "I write it in Thai … then I put in ChatGPT to make it more professional … and check again whether or not it still has the same meaning as when I first wrote this."*
>
> *S07: "Not fully confident to trust everything because… I don't dare to just copy all and submit it."*

Theme 4. Verification ecology: cross-checking with peers and multiple tools

AI was perceived as several potential sources rather than a single reference authority, and hence its accuracy was verified against peers, other AI tools and search engines before content based on AI analysis was taken into account for submission.

> *S03: "I usually send it to a friend to re-check… because my friend understands what the teacher ask better than ChatGPT."*
>
> *S13 [disagreement episode]: "When I felt the AI's information wasn't right, I searched in Gemini and then Google as well."*
>
> *S13 [grammar check episode]: "After I was satisfied, I checked grammar in Google and corrected mistakes in Word."*
>
> *S07: "If I disagreed, I would switch to another app to 'distribute the risk'… mostly ChatGPT and Gemini."*

S07: "ChatGPT is more detailed and feels like talking to a friend… Gemini is broader and more like general principles."

Theme 5. Ethical boundaries, detection awareness, and disclosure

Students articulated a boundary between using AI as a tool and allowing AI to do the work. Some were aware of AI-detection tools and discussed strategies of paraphrasing or rewriting. Views on disclosure varied: some would disclose if asked while others would not inform.

S01: "It's cheating… and nowadays there are AI-detection tools, so we have to change the wording again."

S09 [ethics reflection]: "I don't think it's cheating… AI is similar to Google—it helps us find information, but it compiles it so we don't need to scroll."

S01: "I wouldn't tell them unless they asked—others might be using it too."

Theme 6. Social-cultural dynamics and dependence concerns

Two tendencies manifested themselves. Help-seeking was restrained by social distance and 'kreng jai' worries about over-reliance on authorities. Participants also expressed trepidation about over-reliance and atrophy from skill development should AI usage become excessive.

S09 [AI vs teacher]: "AI feels like a friend… but with a teacher it's more formal and you feel 'kreng jai' because of social status."

S12 [kreng jai example]: "Some things I feel 'kreng jai' to ask a teacher… for example, math. I have my own reasoning, but I ask AI how to think faster."

S09 [dependence anxiety]: "I worry that if I use AI too much, I won't use my brain… I'm afraid my skills will decline."

S07: "Before AI, it was hard to know—you had to ask the teacher only. Now if I don't understand, I ask ChatGPT and I know right away."

S07: "I will keep using it, but I have to look at many things—not just AI only."

C. Integrated Mixed-Methods Findings

Integration considered how qualitative themes account for quantitative findings. Table 5 shows a joint display linking convergent and additional findings across quantitative and qualitative variables.

TABLE 5
JOINT DISPLAY LINKING QUANTITATIVE PATTERNS WITH QUALITATIVE EXPLANATIONS (META-INFERENCES)

Quantitative pattern	Qualitative explanation (theme link)	Integrated meta-inference
D2 (M = 4.69) and D3 (M = 4.44) were higher than D1 (M = 3.65).	AI was used mainly for language polishing and structuring; genre conventions required interpreting models (Themes 1–2).	AI support appears to benefit language/organization more readily than genre-specific moves.
AI acceptance correlated with D3 (PU rho=.319; PEOU rho=.349; TAM rho=.278) but not with D1, D2, or total score.	Students used AI to refine coherence iteratively, but final choices depended on human judgment (Themes 1, 3–4).	Perceived value may translate into clearer organization, while overall quality depends on evaluation and revision skills.
Power distance was strongly associated with AI acceptance (PD–TAM rho=.638).	AI was framed as a low-stakes source of guidance when students felt hesitant to approach authority directly (Theme 6).	Authority-related norms may shape why learners adopt AI tools for writing support.
Collectivism correlated with PU (rho=.498) and ATT (rho=.488).	Peer checking and collaborative verification were common before submission (Theme 4).	Social verification may amplify perceived usefulness and acceptance in collectivist contexts.
Uncertainty avoidance correlated with PU (rho=.332) and ATT (rho=.284), but not with PEOU.	Students emphasised cross-checking and risk reduction via multiple sources (Theme 4).	AI may be valued for reducing ambiguity even when perceived ease of use is unchanged.

Note. Meta-inferences capture convergence and expansion between strands and should be understood as interpretive accounts, not causal claims.

Across strands, common findings included that AI was primarily used as a writing and revision support tool, which is consistent with relatively higher strand scores in D2 and D3. Qualitative analyses of specific instances of AI use, however, offered an extended version of the quantitative findings that included discussions of iterative prompting and verification strategies, as well as voice management strategies, all of which help to account for the reasons that positive views of AI did not manifest in uniformly higher levels of writing quality. Finally, the strong relation between Power Distance and AI acceptance were placed within a frame of authority-sensitive help-seeking ("kreng jai") and the structure of explicit permission frameworks as a means of controlling AI use.

V. DISCUSSION

This mixed-methods study assessed the intersection of Thai EFL learners' acceptance of AI writing support (TAM), cultural orientations, and professional writing quality in English cover letters. Rubric-based assessments demonstrated stronger performance in language accuracy and discourse-level organization than in genre conventions. The central quantitative finding was that technology acceptance was related to organization and coherence, suggesting that the perceived usefulness and ease of use of AI fostered better drafting and revising in those areas rather than even-handed improvements across all writing dimensions.

The relatively weaker and more variable performance in genre conventions (D1) corresponds with ESP/genre perspectives that analyze professional texts as socially-embedded actions whose form is constrained by expectations from discourse communities (Swales, 1990). It also corresponds with cognitive models of writing that see the allocation of cognitive resources as central, with novice writers in particular using up a large proportion of their resources at the sentence level, leaving few resources for decisions about text structure and content selection (Flower & Hayes, 1981). In the context of a cover letter, for example, such models suggest that writers need explicit support in learning how to match their content, moves and formatting to the expectations of a specific job role—when the means of production no longer pose a barrier.

The positive correlations between perceived usefulness/ease of use and organization and coherence (D3) align with TAM's basic claim that usefulness and ease of use facilitate adoption and goal-oriented use (Davis, 1989; Venkatesh & Davis, 2000). This finding corresponds with evidence from AI-aided writing studies showing that learners rely on LLMs to create outlines, build the logic of their writing, and polish paragraph-level coherence (Meniado et al., 2024). The interview data in this study also suggest that many students worked in an iterative "prompt, revise, repeat" fashion so that the AI was serving as a planning and coherence scaffold but not replacing the student's authorial role. It should be clarified, however, that the PU–D3 correlation did not hold when using Pearson's r ($r = .249$, $p = .067$), demonstrating that this r-value is not as strong as PEOU–D3 and TAM–D3, and should be further assessed in future research with larger sample sizes.

Yet, the lack of strong correlations with language accuracy (D2) or total scores contravenes the intuition that AI would primarily improve grammar. This contrasts with the following contextual and measurement-related factors: (a) language accuracy scores may be constrained in variability when many learners have access to the same AI-based proofreading resource, resulting in a lack of signal for correlations; (b) cover letters are assessed on their fit with the audience, credibility, and overall rhetorical moves rather than strict grammatical accuracy. Previous research has similarly established that LLM outputs are not directly usable without human verification and contextualizing for real-world use cases (Özçelik & Ekşi, 2024; Nguyen, 2026). This likely shifted the detectable effect of acceptance toward discourse organization (D3) rather than sentence-level accuracy (D2).

The strong association between power distance and AI acceptance further suggests that legitimacy and explicit classroom framing may be key to acceptance in a Thai EFL context. This finding aligns with earlier extended acceptance models of technology that emphasize socialization and the role of norms in accepting technology (Venkatesh & Davis, 2000). It also aligns with discussions in the Thai learning context that have highlighted concerns about the appropriateness of generative AI use for writing, policy concerns, and ethical boundaries (Buripakdi & An, 2024; Limna & Shaengchart, 2025). There is qualitative evidence of the study indicating that learners would rather ask an AI than an authority, so it becomes crucial for instructors to provide clear instructions as to how and with what confidence to use these programs.

Collectively, the findings suggest several implications for ESP teaching. First, genre still merits instructional attention in terms of rhetorical moves, tone, and format, with model texts and rubric-dependent checklists (Swales, 1990). Second, AI literacy should be taught as part of digital writing, covering effective prompting, verification strategies, voice control, and ethical limits (Meniado et al., 2024). Third, in classrooms where authority matters, teachers may want to stipulate which uses of AI are acceptable, under what conditions, and with what obligations of disclosure, so that students can harness these tools with confidence and responsibility. For RQ1, the findings showed that students harnessed AI as a form of digital scaffolding within a process-based outlining/drafting/revision framework, conditional on verification and voice management. For RQ2, students were generally in favour of AI assistance but expressed reservations about dependence, accuracy, and trust. For RQ3, power distance proved the strongest cultural predictor of AI acceptance, suggesting that teacher-authorized legitimacy is a prerequisite for responsible classroom integration.

VI. CONCLUSION

The conclusions drawn from the results indicate that the Thai EFL learners' uptake of AI writing help is associated with professional standard of writing in a dimension-tailored way. Higher levels of perceived usefulness and ease of use were associated with stronger effects on a preceding measure of topic coherence (D3), while struggles remained with consistency in observing the correct genre features (D1). The qualitative analysis supported these conclusions as prompts, revisions and checks were identified as factors that affected what the feedback did to the learners. As such, the repeated prompting function exemplifies AI-based scaffolding that supports learners' Zone of Proximal Development (Vygotsky, 1978) to develop independent writing abilities.

Methodologically, the findings should be interpreted in light of the limitations of a single-institution study, the reliance on self-report measures, and the correlational structure of the design that precludes causality. Future research could extend the study to a larger number of participants drawn from a wider range of institutional contexts, examine the effects of varying prompting strategies on writing quality, and assess the long-term effects of AI-assisted writing instruction on genre acquisition and authorship development. In the context of ESP instruction, the findings suggest a qualified view of AI's value as a learning tool: AI is shown to be particularly effective as a planning and revision aid, while genre learning still appears to require explicit instruction in rhetorical moves and discourse conventions (Swales, 1990). Yet the influence of cultural norms and perceptions of legitimacy also suggests the need for socially-aware implementation frameworks for Thai EFL classrooms (Venkatesh & Davis, 2000; Buripakdi & An, 2024). Taken together, the findings support the claim that AI can improve discourse-based writing outcomes when properly integrated into professional writing instruction on genre, ethics, and culture.

Appendix A. Additional Illustrative Quotes by Theme

The interviews were in Thai and transcribed verbatim. The excerpts below are in English translation for reporting. Participant identifiers (S01–S13) are used consistently in this manuscript.

Table A
Selected Illustrative Interview Excerpts by Theme (English Translation)

Theme	Extract (ID)	Excerpt
Iterative workflow and task scaffolding	S03	"I start from the job description, list what I have, turn it into a prompt, then iterate—revising and prompting again until it matches what I need."
Lexico-grammatical support and register control	S03	"I mostly use it to check spelling/grammar—wrong tense or strange grammar—rather than letting it write everything."
Human agency and voice preservation	S08	"It doesn't sound human. I fix it myself first; if I can't, I tell it: 'Humans don't say it like this—revise it.'"
Verification ecology: cross-checking with peers and multiple tools	S13	"When I felt the AI's information wasn't right, I checked Gemini and then Google as well."
Ethical boundaries, detection awareness, and disclosure	S01	"It's cheating… and now there are AI-detection tools, so we have to change the wording again."
Social-cultural dynamics and dependence concerns	S09	"AI feels like a friend… but with a teacher it's more formal, and you feel *kreng jai* because of social status."

Appendix B. Robustness Check Correlations and Scale Reliability

Note. The main text reports Spearman's rho (ρ) as the primary analysis. Pearson's r is provided here as a robustness check, alongside internal consistency estimates. Two-tailed p-values are shown in parentheses. Significance markers: * $p < .05$, ** $p < .01$, *** $p < .001$.

Table B1
Pearson Correlations (R) Between AI Perceptions and Cover Letter Scores (N = 55)

Variable	D1	D2	D3	Total
PU	-0.177 (p = .197)	0.078 (p = .573)	0.249 (p = .067)	-0.023 (p = .866)
PEOU	-0.183 (p = .181)	0.201 (p = .142)	0.307* (p = .022)	0.038 (p = .784)
ATT	-0.206 (p = .131)	0.030 (p = .826)	0.169 (p = .218)	-0.093 (p = .499)
TAM	-0.223 (p = .102)	0.121 (p = .377)	0.283* (p = .036)	-0.032 (p = .815)

Table B2
Pearson Correlations (R) Between Cultural Dimensions and AI Perceptions (N = 55)

Variable	PU	PEOU	ATT	TAM
COL	0.386** (p = .004)	0.101 (p = .464)	0.351** (p = .009)	0.323* (p = .016)
PD	0.450*** (p = .001)	0.467*** (p < .001)	0.491*** (p < .001)	0.554*** (p < .001)
UA	0.240 (p = .078)	0.049 (p = .725)	0.163 (p = .234)	0.172 (p = .211)

References

[1] Alharbi, M. A., & Al-Ahdal, A. A. M. H. (2025). Exploring Saudi EFL learners' engagement with ChatGPT: A mixed-methods study of perceptions, attitudes, and intentions. *SAGE Open*, *15*(4). https://doi.org/10.1177/21582440251392080

[2] Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

[3] Buripakdi, A., & An, L. T. (2024). "Why Can't I Use ChatGPT for My Academic Learning?" Voices from Ph.D. students in a Thai university. *LEARN Journal: Language Education and Acquisition Research Network*, *17*(2), 299–319. https://doi.org/10.70730/VRVS6900

[4] Creswell, J. W., & Plano Clark, V. L. (2018). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.
[5] Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008
[6] Flower, L., & Hayes, J. R. (1981). A cognitive process theory of writing. *College Composition and Communication*, *32*(4), 365–387. https://doi.org/10.2307/356600
[7] Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, *18*(1), 59–82. https://doi.org/10.1177/1525822X05279903
[8] Hofstede, G. (2001). *Culture's consequences: Comparing values, behaviors, institutions, and organizations across nations* (2nd ed.). SAGE.
[9] Koo, T. K., & Li, M. Y. (2016). A guideline for selecting and reporting intraclass correlation coefficients for reliability research. *Journal of Chiropractic Medicine*, *15*(2), 155–163. https://doi.org/10.1016/j.jcm.2016.02.012
[10] Limna, P., & Shaengchart, Y. (2025). Generative AI as an English writing aid: Thai university students' perceptions and experiences with ChatGPT and Gemini. *Suranaree Journal of Social Science*, *19*(3), e279466. https://doi.org/10.55766/sjss279466
[11] Meniado, J. C., Huyen, D. T. T., Panyadilokpong, N., & Lertkomolwit, P. (2024). Using ChatGPT for second language writing: Experiences and perceptions of EFL learners in Thailand and Vietnam. *Computers & Education: Artificial Intelligence*, *7*, 100313. https://doi.org/10.1016/j.caeai.2024.100313
[12] Nguyen, T. D. H. (2026). EFL students' attitudes towards the use of ChatGPT in learning how to write essays: Vietnamese context. *Theory and Practice in Language Studies*, *16*(2), 464–472. https://doi.org/10.17507/tpls.1602.13
[13] Özçelik, N. P., & Ekşi, G. Y. (2024). Cultivating writing skills: The role of ChatGPT as a learning assistant—A case study. *Smart Learning Environments*, *11*, 10. https://doi.org/10.1186/s40561-024-00296-8
[14] Sanderson, I. J., & Stephens, O. S. (2023). ความถี่และความแม่นยำของการตอบสนองและคำแนะนำจากฟรีแกรมมาลี (Free Grammarly) ในการช่วยแก้ไขข้อผิดพลาดในการเขียนภาษาอังกฤษของนักศึกษาไทยในระดับมหาวิทยาลัย [The frequency and accuracy of prompts and suggestions made by free Grammarly on Thai university students' English writing errors]. *มนุษยศาสตร์สาร มหาวิทยาลัยเชียงใหม่,* [Chiang Mai University Journal of Humanities], *24*(3), 257–294.
[15] Shrout, P. E., & Fleiss, J. L. (1979). Intraclass correlations: Uses in assessing rater reliability. *Psychological Bulletin*, *86*(2), 420–428. https://doi.org/10.1037/0033-2909.86.2.420
[16] Swales, J. M. (1990). *Genre analysis: English in academic and research settings*. Cambridge University Press.
[17] Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926
[18] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540
[19] Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes* (M. Cole, V. John-Steiner, S. Scribner, & E. Souberman, Eds.). Harvard University Press.
[20] Wood, D., Bruner, J. S., & Ross, G. (1976). The role of tutoring in problem solving. *Journal of Child Psychology and Psychiatry*, *17*(2), 89–100. https://doi.org/10.1111/j.1469-7610.1976.tb00381.x
[21] Yoo, B., Donthu, N., & Lenartowicz, T. (2011). Measuring Hofstede's five dimensions of cultural values at the individual level: Development and validation of CVSCALE. *Journal of International Consumer Marketing*, *23*(3–4), 193–210. https://doi.org/10.1080/08961530.2011.578059

Pimpisa Chanted was born in Phitsanulok, Thailand. She received her B.A. in English for Specific Purposes from King Mongkut's Institute of Technology Ladkrabang in 2004, and her M.A. in English for Careers from Thammasat University in 2013.

She is currently a lecturer at the Faculty of Management Sciences, Kasetsart University, Sriracha Campus, Chonburi, Thailand. Her selected publications include: Chanted, P. (2025). The role of technical communication and relevance of English vocabulary of university students. Sripatum Chonburi Academic Journal, 21(1), 146–157; Chanted, P., Gururatana, S., Perrin, R., & Orkphol, K. (2023). Using data-driven analysis to determine the launching of an English course for the tourism industry in Hua Hin, Thailand. In Proceedings of the 15th ECTI-CARD 2023 (Hua Hin, Thailand); and Chanted, P., Orkphol, K., Perrin, R., & Gururatana, S. (2023). Predicting total flight numbers in Thailand during the post-COVID-19 period using FBprophet and Neural-Prophet. Buriram Rajabhat University Journal of Research and Development, 18(1), 35–46. She also teaches English for Health Service Business and related courses. Her research interests include EFL writing instruction, AI-assisted learning tools, professional writing assessment, and applied data analytics. She can be reached at Pimpisa.chan@ku.th (ORCID iD: 0009-0008-2873-8011).