JOLLS: Journal of Language and Literature Studies
Website: https://journal-center.litpam.com/index.php/jolls/index
Email: jolls@litpam.com
DOI: https://doi.org/10.36312/jolls.v6i2.4944

June 2026 Vol. 6, No. 2
e-ISSN: 2808-1099
pp. 753-765

Patterns of AI Integration in Literary Translation: Student Translators' Outputs and Strategies

Lia Agustina Damanik
Tadris Bahasa Inggris, STAIN Mandailing Natal, Panyabungan, Jln. Prof. Dr. Andi Hakim Nasution, Panyabungan, Mandailing Natal, North Sumatera, Indonesia

Corresponding Author e-mail: liaagustinadamanik@stain-madina.ac.id

Received: April 2026; Revised: May 2026 ; Accepted: May 2026; Published: June 2026

Abstract

As AI translation tools increasingly enter translator training, understanding how students use them critically especially in literary translation has become essential. Literary texts require nuanced handling of culture, figurative language, and style, areas where raw AI output often fails. This qualitative descriptive study examined AI integration patterns among 18 undergraduate literary translators. With AI permitted, students completed five tasks: narrative analysis, element mapping, glossary building, translation, and written strategy justification. Open coding and textual triangulation revealed five patterns: (1) prioritizing communicative meaning, (2) domesticating while retaining cultural terms, (3) preserving religious-cultural elements, (4) documenting techniques item by item, and (5) producing strong outputs with minimal justification. A critical finding: translation quality alone cannot detect AI use; only written justifications make it visible. A three-tier developmental framework emerged: Exceptional (28%; 93–97/100), Strong (44%; 83–90/100), and Incomplete (28%; 37–65/100). Tier placement depended primarily on explicit grounding in translation theory (Newmark, Baker, Venuti). Theory-grounded students used AI more reflectively, treating outputs as provisional, recognizing untranslatability, and preserving cultural-spiritual concepts. Two phenomenological case studies (S1, S2) showed that translation excellence follows complementary pathways, with theoretical grounding as the common mechanism enabling critical AI use. The study recommends task designs that demand reflective transparency and pre-task theoretical instruction to foster critical AI literacy in literary translation pedagogy.

Keywords: AI literacy; Literary translation; Translation pedagogy; Critical AI use; Translation strategy

How to Cite: Damanik, L.A. (2026). Patterns of AI Integration in Literary Translation: Student Translators' Outputs and Strategies. *Journal of Language and Literature Studies, 6*(2), 753-765. doi: https://doi.org/10.36312/jolls.v6i2.4944

https://doi.org/10.36312/jolls.v6i2.4944

INTRODUCTION

The rapid integration of artificial intelligence (AI) into higher education has reshaped how translation is taught, practiced, and assessed, particularly as students increasingly rely on neural machine translation (NMT) engines and large language models (LLMs) for academic and professional tasks (Liu & Afzaal, 2021; Aleedy et al., 2025; Sohail & Zhang, 2025; Wang & Fan, 2025). In translator training, these tools are no longer peripheral aids but part of students' everyday workflows. Their presence requires researchers to move beyond asking whether AI can produce accurate translations and instead examine how student translators interpret, revise, and justify machine-generated suggestions. This issue is especially important in literary translation, where meaning depends on style, voice, rhythm, cultural reference, and affective force. Because literary texts demand interpretive sensitivity and creative decision-making, they provide a demanding context for evaluating AI-assisted translation practices (Egdom et al., 2024; Naeem et al., 2025). Student translators therefore represent a critical group for understanding how human agency and machine assistance interact in contemporary translation education (Belhassen & Hamda, 2025).

Although scholarship on AI-supported translation has expanded, much existing empirical work still emphasizes output quality, accuracy metrics, or language proficiency outcomes. Such studies are useful, but they do not fully explain the processes through which students use AI or the reasoning that guides their decisions (Lee, 2021). A central pedagogical concern is that students may treat AI as an opaque "black-box" translator, accepting machine-generated drafts without sufficient source-text analysis, stylistic evaluation, or cultural reflection. When only final translations are assessed, AI use becomes difficult to trace, and instructors cannot determine whether a strong output results from strategic post-editing, uncritical acceptance, or independent human decision-making. This limitation highlights the need for qualitative research that examines both what students produce and how they explain their choices. Studying outputs alongside written strategy justifications can reveal students' AI literacy, metacognitive awareness, and ability to connect technology use with established translation theories (Ibrahim, 2024; Abdelhalim et al., 2025).

This study is situated within literary translation pedagogy, where translation is understood as rewriting rather than simple transfer. Literary translators negotiate semantic content, stylistic form, cultural meaning, and reader response simultaneously (Baker, 2011; Venuti, 2017). Newmark's (1988) distinction between semantic translation, which emphasizes source-text nuance, and communicative translation, which prioritizes naturalness and target-reader effect, remains useful for analyzing students' choices in AI-assisted translation. Recent pedagogical discussion shows that this distinction helps students evaluate procedures such as literal translation, modulation, cultural substitution, and explicitation (Al Awdi, 2025). Similarly, Venuti's (2017) concepts of domestication and foreignization clarify how translation decisions are shaped by ideological and cultural positioning. In culturally embedded texts, students must decide whether to preserve source-culture specificity through foreignizing strategies or adapt expressions to target-culture expectations through domestication. AI-generated suggestions may be fluent, but fluency alone does not guarantee cultural adequacy, stylistic fidelity, or ethical awareness.

Process-oriented translation research further supports the need to investigate how students arrive at their final texts. Translation is widely recognized as a cyclical, problem-solving activity involving comprehension, transfer, drafting, evaluation, and revision rather than a linear replacement of words across languages (Baker, 2011). Studies using think-aloud protocols and keystroke logging show that novice translators repeatedly return to earlier decisions as new problems emerge (González Davies & Scott-Tennent, 2005). Developing translation competence therefore involves the ability to identify problems, compare alternatives, manage resources, and justify decisions (Xiao & Zeng, 2023). In pedagogical contexts, tasks that require students to articulate the reasons behind their choices deepen awareness of how strategies shape meaning, voice, and reader effect (Hajmalek & Aghamohammadi, 2023). This reflective dimension is significant when AI tools are involved because students must learn to use AI efficiently while evaluating its limitations critically.

In translator education, AI is increasingly framed as a resource that must be used transparently, selectively, and critically rather than as an automatic substitute for human judgment (Ibrahim, 2024). Research suggests that AI tools can support initial drafting, lexical exploration, phraseological variation, and post-editing practice, especially when learners compare machine suggestions with source-text demands and target-reader expectations (Lee, 2021). However, unguided AI use may encourage over-reliance, superficial source-text engagement, and reduced ownership of the translation process, particularly among novice translators (Kornacki, 2025). These risks become more pronounced in literary translation because AI-generated drafts often struggle with narrative voice, figurative language, implied meaning, and culturally embedded resonance (Zulkifli, 2025). For this reason, AI-assisted literary translation classrooms require task designs that make decision-making visible. Students should explain when AI suggestions are useful, when they are inadequate, and how revisions are informed by concepts such as equivalence, semantic and communicative translation, domestication, and foreignization (Newmark, 1988; Venuti, 2017).

Recent studies on AI-mediated learning emphasize reflection and metacognition as indicators of meaningful technology use. Written strategy justifications provide access to students' reasoning about problem identification, strategy selection, and AI's role within decision-making (Wutich et al., 2024). Student translators may integrate AI in different ways: some begin with AI-generated drafts and revise extensively; others use AI selectively as a dictionary, phrase bank, or idea generator; and others translate independently before consulting AI for verification or refinement (Ibrahim, 2024). These patterns cannot be understood through outputs alone. They become clearer when translations are triangulated with students' explanations of how they accepted, rejected, modified, or departed from machine suggestions (Kornacki, 2025). The depth of these justifications may range from descriptive accounts of tool use to theory-informed reflections that reveal students' agency and professional identity in technology-mediated environments (Alaa & Al Sawi, 2023; Abdelhalim et al., 2025).

The novelty of this study lies in its focus on patterns of AI integration and strategy justification in student literary translation rather than on judging whether AI-assisted translations are simply good or bad. By examining the relationship between translation outputs and written explanations, the study foregrounds the processual, reflective, and theory-grounded dimensions of AI-assisted translator training. It also contributes pedagogically by showing how curriculum design can support critical AI literacy and prevent unreflective dependence on automated translation. Accordingly, this research aims to map how student translators use AI tools in literary translation, how their AI use is reflected in translated texts and written justifications, and how theory-grounding can explain differences in performance. To achieve these objectives, the study addresses the following research questions: 1. What patterns of AI integration can be identified in student translators' literary translation outputs, and how do these patterns reflect students' engagement with, or departure from, AI-generated suggestions? 2. How are these patterns manifested in students' written strategy justifications, and what does the relationship between outputs and justifications reveal about critical AI literacy? 3. What explains differential performance across students, and how can theory-grounding be developed through curriculum design to enable critical, reflective AI use?

METHOD

Research Design

This study employs a qualitative descriptive design, which is particularly suitable for examining students' reasoning, translation strategies, and AI-use patterns because it prioritizes a rich, contextualized understanding of phenomena as they naturally occur without manipulating variables or testing hypotheses (Ibrahim, 2024).Unlike experimental or quasi-experimental designs that seek causal relationships or comparative effectiveness, a qualitative descriptive design allows the researcher to stay close to the data and to participants' own accounts of their decision-making processes. This design is therefore appropriate for capturing how student translators articulate their integration of AI tools, the strategic choices they make, and the ways they justify or reflect on those choices—

areas that are difficult to quantify but essential for understanding critical AI literacy in literary translation pedagogy(Xiao & Zeng, 2023).

Participants

The study involved 18 semester-5 undergraduate students enrolled in a Translation: Indonesian-English course at a state university in Indonesia located in a region with limited access to urban educational facilities. Participants' ages ranged from 20 to 23 years (mean = 21.2 years). Gender distribution was 13 female (72.2%) and 5 male (27.8%), reflecting the typical gender composition of the English department at the institution. Students' English language proficiency, as measured by institutional placement tests and previous semester grades in English language skills courses, ranged from A2 to B1 (CEFR), with most students (13 out of 18) scoring at the B1 level and the remaining five at A2.

The proficiency profile is characteristic of the region, where access to English-language media, native-speaker interaction, and formal language training is constrained by geographic and socioeconomic factors. Prior translation experience was limited to two semesters of introductory translation courses focusing on non-literary texts (e.g., news articles, instruction manuals, short business correspondence). None of the students had completed a dedicated literary translation course before this study. Prior AI experience varied: all 18 students reported using Google Translate for word-level or phrase-level assistance in previous coursework; 12 reported using ChatGPT for academic writing or translation tasks; and 5 reported using other AI tools such as DeepL or Bing Translator. However, none had received formal instruction on critical AI use or on integrating AI tools into literary translation workflows.

Ethical consent procedures followed the institutional review board guidelines of the university. All participants were informed of the study's purpose, the voluntary nature of participation, and their right to withdraw at any time without academic penalty. Written informed consent was obtained from all 18 students prior to data collection. Students were assured that their translation outputs and justifications would be used for research purposes only after the course grades had been finalized, and that identifying information would be anonymized in any publication. Pseudonyms (e.g., S1, S2, S3, S4) are used throughout this report.

Instruments

The study employed several instruments and data tools, which are described below: First, the researcher applied five-Component Translation Task. Students completed a structured task comprising: narrative analysis (identifying key events, characters, and plot structure of the source text), element mapping (matching cultural references, idioms, and stylistic features to potential target-language equivalents), glossary construction (creating a list of 10-15 key terms with proposed translations and rationales), translation (producing a complete English translation of the 5-8 page literary text), and (e) written strategy justification (a 200-500 word reflective essay). This task design was developed by the researcher to align with process-oriented translation pedagogy (González Davies & Scott-Tennent, 2005). Second, the researcher applied written Strategy Justification Prompt: Students responded to the open-ended prompt: "Why did you decide to translate the text in this way? Please describe your process, including any AI tools you used (e.g., ChatGPT, Google Translate), when you used them, how you evaluated their suggestions, and what changes you made." This prompt served as the primary instrument for capturing students' reasoning and AI-use transparency. Third, the researcher applied scoring rubric and performance tiers: A 100-point scoring rubric was developed, allocating points across: task completion (20 points), translation accuracy and readability (30 points), handling of cultural and figurative language (20 points), depth of strategy justification (15 points), and explicit theory grounding (15 points). Based on total scores, students were classified into three performance tiers: Exceptional (93–97/100), Strong (83–90/100), and Incomplete (37–65/100).

Fourth, the research used coding categories for AI Integration Patterns: An inductive coding scheme was developed through open coding, comprising five main patterns: (a) communicative-first positioning, (b) domestication plus retention for cultural terms, (c) religious-cultural and customs preservation, (d) itemized technique documentation, and (e) strong output with minimal justification. Fifth, the researcher applied assessment notes. The researcher maintained summary notes during the grading process, recording observations about each student's translation choices, recurrent errors, and notable strategies. Oral Clarification Protocol: For member checking, brief oral conversations (5-10 minutes each) were conducted with 4 students whose justifications showed distinctive patterns, to affirm, clarify, or correct initial interpretations.

Data Collection Technique

Data collection proceeded step by step as follows: Step 1 – Source Text Selection: The researcher selected a 7-page Indonesian short story entitled "Pulang" (author anonymized for review). The text was chosen for its richness in cultural references (e.g., Javanese traditional ceremonies, kinship terms, religious expressions), figurative language (metaphors, similes, proverbs), and narrative voice (first-person reflective tone). The text length (approximately 2,100 words) was deemed appropriate for a 2-3 week assignment at the students' proficiency level.

Step 2 – Task Duration and AI Permission: Students were given 2.5 weeks to complete all five task components. At the outset, they were explicitly informed that AI tools (including ChatGPT, Google Translate, DeepL, Bing Translator, and similar platforms) were permitted as allowed resources throughout the entire process—from initial reading and comprehension through drafting, revision, and final polishing. This permission was stated in writing on the assignment instruction sheet and reiterated verbally in class. However, students were also advised that AI should not be used as a primary strategy without critical evaluation, and that they would be required to document their AI use in the written justification.

Step 3 – Submission Procedure: Students submitted their completed tasks (narrative analysis, element mapping, glossary, translation, and written justification) as a single PDF file through the university's learning management system (LMS). Submissions were timestamped, and late submissions (none in this cohort) would have incurred a penalty. Step 4 – Collection of Translation Outputs: Each student's English translation of the 7-page story was extracted from the submitted PDF and saved as a separate document for analysis. Translations were analyzed for handling of metaphors, figurative language, cultural terms, and sentence-level structure. Step 5 – Collection of Written Justifications: The final section of each submission (200-500 words) was extracted and compiled into a separate document for open coding. Justifications were analyzed for mentions of AI tools, stages of use, evaluation of AI output, and theory references.

Step 6 – Member Checking: After preliminary pattern identification, the researcher conducted brief oral conversations (5-10 minutes each) with 4 students (S1, S2, S3, S4). During these sessions, the researcher summarized the identified pattern for each student and asked clarifying questions such as: "You mentioned using ChatGPT for the glossary—can you tell me more about how you decided which terms to keep versus change?" Students confirmed, clarified, or corrected the researcher's interpretations. These conversations were not recorded but summary notes were added to the audit trail.

Data Analysis Technique

Data analysis followed a systematic, iterative process: Phase 1 – Open Coding of Written Justifications: All 18 written justifications were read multiple times. Open coding was performed line by line, marking every instance of: (a) specific AI tools named (e.g., ChatGPT, Google Translate), (b) stage of process when AI was invoked (e.g., initial comprehension, drafting, revision, polishing), (c) translation problem or decision that prompted AI use (e.g., unknown vocabulary, idiom, cultural term, sentence restructuring), (d) whether students followed, modified, or rejected AI output, and (e) reasoning offered for accepting or changing suggestions. Codes were recorded in a coding table with excerpts.

Phase 2 – Pattern Development: Codes were inductively synthesized to identify emergent patterns of AI integration. Through iterative comparison and grouping of similar codes, five distinct patterns emerged: (1) communicative-first positioning (prioritizing natural target-language expression over literal accuracy), (2) domestication plus retention for cultural terms (adapting structure while preserving key cultural items), (3) religious-cultural and customs preservation (maintaining source-culture spiritual concepts even at cost of readability), (4) itemized technique documentation (listing specific translation techniques with brief explanations), and (5) strong output with minimal justification (producing high-quality translations but offering little or no reasoning).

Phase 3 – Triangulation with Translation Outputs: For each identified pattern, the corresponding translation outputs were examined for corroborating evidence. Specifically, the researcher analyzed: (a) handling of metaphors and figurative language (preserved literally, adapted with target-language equivalent, or replaced with non-figurative phrasing), (b) handling of cultural terms (translated literally, domesticated, foreignized with glossary, or omitted), and (c) sentence-level structure (rendered parallel to source syntax or reconfigured for English naturalness). Discrepancies between justification claims and output features were noted as potential areas for further inquiry.

Phase 4 – Theory Grounding Coding: A secondary analytical pass coded all justifications for: (a) depth of reflection (descriptive: stating what was done without reasoning; evaluative: weighing options and consequences; critically reflective: evaluating choices against theoretical frameworks or literary text demands), and (b) presence and sophistication of translation theory reference (0 = no theory reference; 1 = named a theorist or concept without elaboration; 2 = applied a theoretical concept to a specific translation decision). This coding operationalized the distinction between atheoretical practice and theory-grounded practice.

Phase 5 – Tier Classification: Based on total scores from the scoring rubric, all 18 students were classified into three performance tiers: Exceptional (N=5; scores 93-97/100; explicit and sophisticated theory reference, deep justification, high-quality translation), Strong (N=8; scores 83-90/100; named strategies with moderate reasoning, good translation quality), and Incomplete (N=5; scores 37-65/100; minimal or absent justification, incomplete submission, or major translation errors).

Phase 6 – Case Selection for Phenomenological Analysis: From the 18 students, 4-6 purposively selected cases were chosen for detailed phenomenological analysis. Selection criteria were: (a) distinctive patterns in written justifications (e.g., one student demonstrated exceptionally deep theory grounding; another showed minimal justification despite strong output), and (b) representativeness of the three performance tiers. Ultimately, 4 students (S1, S2, S3, S4) were selected: S1 (Exceptional, critically reflective), S2 (Exceptional, different pathway), S3 (Strong, moderate reflection), S4 (Incomplete, minimal justification). For each selected case, a detailed narrative was constructed describing the student's pattern of AI integration, supported by quotations from justifications and examples from translation outputs.

Phase 7 – Trustworthiness Procedures: Trustworthiness was enhanced through: (a) triangulation of written justifications, translation outputs, and assessment notes; (b) member checking with 4 students (S1–S4) to verify interpretations; (c) an audit trail retaining all coded documents, analytical memos, and pattern categories in chronological order; (d) reflexivity, acknowledging the researcher's dual role as course instructor, with deliberate attention to disconfirming evidence (e.g., cases where justification claims contradicted output features were not discarded but analyzed as potential areas of misalignment).

In the initial analysis, two students (S1 and S2) were identified as the primary "excellent" cases, both scoring in the Exceptional tier (93-97/100) but following different pathways. S1 demonstrated a theory-driven, critically reflective approach with substantial revision of AI output. S2 demonstrated an intuitive, aesthetically driven approach with selective AI consultation. These two students were therefore highlighted in the abstract as the core phenomenological cases.

RESULTS AND DISCUSSION

Results

Patterns of AI Integration in Student Translators' Literary Translation Outputs

Among the 18 student translators, scores ranged from 37/100 to 97/100, with a median of approximately 90/100. More important than raw scores, the completeness of the five-component task (narrative analysis, element mapping, glossary, translation, and strategy justification) proved to be the key differentiator for making AI use analytically visible. Students who submitted all components generated sufficient evidence to trace how AI tools entered their workflows, whereas two students who submitted only analytical components (37/100 and 40/100) left their translation processes, including any AI use, effectively opaque.

Table 1. Patterns of AI Integration in Student Literary Translation Outputs

Pattern	Defining Characteristics	Observed Distribution
(1) Communicative-first positioning	Prioritizes target-language naturalness and reader effect; metaphors adapted, syntax restructured	Primarily in Exceptional and Strong tiers
(2) Domestication plus retention for cultural terms	Adapts sentence structure while preserving key cultural items (e.g., kinship terms, local objects)	Across all tiers, but most sophisticated in Exceptional
(3) Religious-cultural and customs preservation	Maintains source-culture spiritual concepts even at cost of readability; often uses foreignization with glossary	Concentrated in Exceptional tier (e.g., S3)
(4) Itemized technique documentation	Lists specific translation techniques (e.g., modulation, amplification) with brief rationales	Common in Strong tier
(5) Strong output with minimal justification	Produces high-quality translation but offers little or no reasoning about AI use	Observed in 2 students (Strong tier); pattern only detectable via product analysis

Across tiers, translation outputs showed recurrent loci where AI integration was most consequential: handling of metaphors and figurative language, sentence-level structuring, and treatment of culturally embedded terms. In the Exceptional and Strong tiers, students' final English versions typically departed in systematic ways from machine-like renderings. These features *suggested* that, where AI was used, its output was subsequently reworked to meet literary and cultural expectations. However—consistent with RQ2—patterns in the product could only be confidently interpreted when triangulated with written justifications.

Reflection of AI Integration Patterns in Written Strategy Justifications

Open coding of all 18 justifications traced every mention of AI across five dimensions: (1) tools named, (2) stage of use, (3) problem prompting use, (4) whether suggestions were followed, modified, or rejected, and (5) reasoning given. From these codes, three behavioral patterns of AI use emerged: AI-first drafting with substantial human revision – Students generated initial drafts with ChatGPT or Google Translate, then substantially reworked structure, lexis, and style. AI as consulted resource for specific phrases/problems – Students used AI selectively to test alternatives or resolve local issues, integrating suggestions into largely human-crafted drafts. Minimal AI use for verification – Students translated primarily by hand, consulting AI only to confirm vocabulary or phrasing.

Table 2. Relationship Among Reflective Level, Theory Reference, and Performance Tier

Performance Tier	N	Predominant Reflective Level	Theory Reference (0–2 scale, mean)	Mean Justification Length (words)
Exceptional (93–97)	5	Critically reflective	1.8	412
Strong (83–90)	8	Evaluative	1.1	287
Incomplete (37–65)	5	Descriptive or absent	0.2	94

A particularly salient finding—termed AI dependency inversion—emerged from cross-tabulating theory reference with AI consultation frequency and acceptance rates. Students with the strongest theoretical grounding (e.g., explicit reference to Newmark, Baker, or Venuti) reported consulting AI more frequently across their workflow, yet accepted a smaller proportion of AI suggestions unchanged. Their justifications documented higher rates of modification and rejection, guided by considerations such as reader effect, cultural specificity, and narrative voice. Conversely, students with weak or absent theory reference consulted AI less often but accepted a much higher proportion of suggestions without explicit evaluative criteria. Thus, theoretical awareness was associated not with avoiding AI, but with *more frequent and more critical* use of AI as a resource.

In summary, RQ2 findings indicate that written justifications do more than document what students did—they index different degrees of metacognitive control over AI. Where justifications are detailed, theory-informed, and explicitly linked to textual choices, AI appears as a tool subsumed under a human translational vision. Where justifications are brief and atheoretical, AI—if present—tends to be either unacknowledged or accepted largely at face value.

Differential Student Performance and Development of Theory-Grounding through Curriculum Design

A three-tier developmental framework (Exceptional, Strong, Incomplete) emerged, with tier placement determined primarily by explicit grounding in translation theory rather than by AI use frequency. Two case studies (S3, S4) demonstrated complementary pathways to excellence—one through cultural-spiritual ethics and foreignization, the other through methodological comprehensiveness and systematic documentation. Both shared high metacognitive control. The findings suggest that theory-grounding is a pedagogically shapeable capacity, not a fixed trait.

Table 3. Three-Tier Developmental Framework

Tier	N	Score Range	Defining Characteristics
Exceptional	5	93–97/100	Full task completion; explicit, sophisticated theory reference (multiple theorists); critically reflective justifications; strong cultural-spiritual awareness; AI output treated as provisional

Tier	N	Score Range	Defining Characteristics
Strong	8	83–90/100	Full task completion; strategy naming with moderate justification; evaluative reflection; competent translation quality; AI used selectively
Incomplete	5	37–65/100	Partial submissions (analytical components only, minimal translation, or truncated justifications); minimal or absent theory reference; descriptive or no reflection; AI use patterns difficult or impossible to trace

A 42-point gap between the highest and lowest tiers was strongly associated with the presence or absence of explicit theoretical framing, extended justification, and critical handling of AI. However, the data also indicated that excellence is not monolithic. Two anonymized case studies from the Exceptional tier illustrated complementary pathways. These cases *suggest* that multiple pathways to excellence exist: one anchored more explicitly in theoretical-philosophical reflection and cultural ethics, the other in procedural rigor and comprehensive execution. Both, however, share a high degree of metacognitive control and an ability to position any AI assistance within a broader translational rationale. The results highlight the broader contribution of literary translation as a site for AI literacy development. Because literary translation foregrounds style, voice, and cultural nuance that current AI systems handle only partially, it naturally compels students to confront the limits of automated output. When students explain why a metaphor is adapted rather than translated literally, or why a cultural term is retained rather than domesticated, they are simultaneously learning to interrogate AI-generated language and to justify their own interventions.

Discussion

The findings of this study show that AI integration in literary translation cannot be understood merely by examining the quality of students' final translations. Instead, AI use becomes visible only when translation outputs are read together with written strategy justifications. This finding confirms previous process-oriented research which argues that translation is not a linear transfer of meaning but a recursive problem-solving activity involving comprehension, drafting, evaluation, revision, and justification (González Davies & Scott-Tennent, 2005; Baker, 2018). In the present study, students who submitted complete task components made their translation processes more traceable, while students with incomplete or brief justifications left their AI use largely invisible. This supports Ibrahim's (2024) argument that AI use in translation education must be studied through learners' decision-making processes, not only through final products. It also extends Lee's (2021) observation that machine translation can support language learning by showing that its pedagogical value depends on whether students can critically explain how, when, and why they use machine-generated suggestions.

The first major finding was the emergence of five patterns of AI integration: communicative-first positioning, domestication with retention of cultural terms, religious-cultural preservation, itemized technique documentation, and strong output with minimal justification. These patterns demonstrate that students did not use AI in a uniform way. Rather, AI functioned variously as a drafting engine, lexical support, verification tool, and stimulus for reflection. This confirms Ibrahim's (2024) claim that students' engagement with AI tools varies according to task demands and individual strategic awareness. However, the present study extends this claim by showing that literary translation creates a particularly demanding environment for AI integration because students must negotiate fluency, cultural meaning, figurative language, and narrative voice simultaneously. This aligns with Egdom et al. (2024), who argue that literary machine translation requires careful prompting and human intervention, and with Naeem et al. (2025), who emphasize that literary translation remains a complex domain where AI cannot fully replace human interpretive judgment.

The communicative-first pattern found among higher-performing students supports Newmark's (1988) distinction between semantic and communicative translation. Students who prioritized reader effect often restructured sentences, adapted metaphors, and modified literal machine-like renderings to produce more natural target-language prose. This confirms Newmark's view that communicative translation is necessary when strict literal transfer would reduce readability or weaken the intended effect. At the same time, the finding extends Al Awdi's (2025) discussion of equivalence by demonstrating that students' ability to balance semantic accuracy and communicative effect is strengthened when they explicitly use theory as a decision-making lens. In this sense, AI did not automatically produce communicative translation; rather, students had to evaluate whether AI suggestions achieved the desired reader response.

The second pattern, domestication combined with retention of cultural terms, confirms Venuti's (2017) argument that translation choices are never neutral. Students who retained culturally specific terms while adapting sentence structure showed awareness that literary translation involves both accessibility and cultural responsibility. This finding is consistent with González Davies and Scott-Tennent's (2005) student-centred approach to translating cultural references, where learners must solve cultural problems rather than simply replace words. It also supports Baker's (2018) view that equivalence is context-dependent and must be negotiated at lexical, pragmatic, and cultural levels. The present study extends these perspectives by showing that AI-assisted translation can either support or weaken cultural mediation depending on students' critical awareness. When students accepted fluent AI suggestions without reflection, cultural specificity tended to be reduced. When they evaluated AI output through concepts such as domestication, foreignization, and equivalence, cultural meaning was more likely to be preserved.

The finding on religious-cultural and customs preservation is especially significant. Students in the Exceptional tier often retained spiritual and ritual terms even when doing so made the English translation less immediately transparent. This confirms Venuti's (2017) argument that foreignization can resist the erasure of cultural difference. It also supports Zulkifli's (2025) claim that AI systems often struggle with culturally embedded and literary meanings. In this study, the strongest students recognized that some concepts could not be fully translated through direct equivalence. Instead of forcing inaccurate target-language substitutes, they used glossaries, explanations, or retained source-language terms. This extends previous research by showing that critical AI literacy in literary translation includes the ability to recognize untranslatability and to justify why preserving difference may be more appropriate than producing a smooth but culturally flattened translation.

The second major finding concerns written strategy justifications. Students' justifications revealed three reflective levels: descriptive, evaluative, and critically reflective. This confirms Wutich et al.'s (2024) emphasis on reflection as a means of accessing learners' reasoning and supports Beeby et al.'s (2003) model of translation competence, which treats strategic competence as central to translator development. Students in the Exceptional tier did not merely report that they used ChatGPT or Google Translate; they explained how they evaluated, modified, or rejected AI suggestions. This finding extends Kornacki's (2025) warning about the risks of uncritical AI use by showing that reflective justification can reduce such risks. When students were required to explain their decisions, AI became less of a hidden shortcut and more of a resource subjected to human evaluation.

A particularly important contribution of this study is the finding described as "AI dependency inversion." Students with stronger theoretical grounding consulted AI more frequently but accepted fewer suggestions unchanged. This complicates the common assumption that frequent AI use necessarily indicates dependence. Previous studies have warned that AI may encourage over-reliance, superficial engagement, or reduced learner ownership (Kornacki, 2025; Belhassen & Hamda, 2025). The present findings partly confirm this concern among students with weak or absent theoretical grounding. However, they also contradict a simplistic view of AI use as inherently passive. For theory-grounded students, frequent AI consultation did not mean surrendering judgment. Instead, AI suggestions became provisional options to be tested against criteria such as reader effect, narrative voice, collocational naturalness, cultural specificity, and theoretical appropriateness. This extends Wang and Fan's (2025) discussion of AI-supported learning by showing that the effect of AI depends strongly on learners' higher-order thinking and evaluative control.

The three-tier developmental framework—Exceptional, Strong, and Incomplete—further demonstrates that performance differences were shaped less by whether students used AI and more by how they positioned AI within a theory-informed translation process. This finding supports Xiao and Zeng's (2023) view that translation competence develops through strategic awareness and problem management. Students in the Exceptional tier showed full task completion, deep reflection, and explicit theoretical grounding, while students in the Incomplete tier often lacked sufficient justification for their choices. This confirms Hajmalek and Aghamohammadi's (2023) argument that task-based translation instruction can strengthen students' awareness when learners are required to articulate their strategies. The present study extends this argument by showing that in AI-rich classrooms, task design must require reflective transparency so that both instructors and students can distinguish critical AI use from unexamined machine dependence.

The case evidence also shows that excellence in AI-assisted literary translation is not monolithic. Some students achieved high performance through cultural-spiritual sensitivity and foreignization, while others did so through systematic documentation and procedural completeness. This finding extends previous work by demonstrating that theory-grounded AI literacy can develop through multiple pathways. What united the strongest students was not a single translation style, but metacognitive control: they could explain their choices, connect them to theory, and subordinate AI output to a broader translational purpose. This supports Newmark's (1988), Baker's (2018), and Venuti's (2017) shared emphasis on the translator's active role in shaping meaning.

The findings confirm that AI can be pedagogically useful in translator training, but only when embedded in tasks that require critical evaluation, theoretical grounding, and written justification. The study extends existing research by showing that literary translation is a productive site for developing critical AI literacy because its demands exceed simple accuracy and fluency. In literary contexts, students must decide how to handle ambiguity, metaphor, rhythm, cultural references, and spiritual meanings—areas where AI output often requires human revision. Therefore, the main implication is that translation pedagogy should not ban AI or accept it uncritically. Instead, instructors should design assessments that require students to document AI use, compare alternatives, justify revisions, and apply translation theory to concrete textual decisions.

CONCLUSION

The discussion demonstrates that AI integration in literary translation is not determined simply by students' access to or frequency of use of AI tools, but by the depth of their reflective and theoretical engagement with those tools. The findings confirm previous studies that emphasize the value of AI in supporting drafting, lexical exploration, and translation revision, while also supporting concerns that uncritical use may lead to dependence, superficial processing, and cultural loss. However, this study extends earlier research by showing that students with stronger grounding in translation theory used AI more critically, not less frequently. Their ability to evaluate, modify, or reject AI-generated suggestions was shaped by concepts such as semantic and communicative translation, equivalence, domestication, and foreignization. Thus, AI-assisted translation quality depends less on the tool itself than on students' capacity to position AI output within a human, theory-informed decision-making process.

The study also concludes that literary translation provides a productive pedagogical context for developing critical AI literacy because it requires attention to meanings that automated systems often handle inadequately, including metaphor, rhythm, narrative voice, cultural specificity, and religious-spiritual concepts. The three-tier developmental framework identified in this study—Exceptional, Strong, and Incomplete—shows that written strategy justification is essential for making AI use visible and assessable. Without such justification, instructors cannot determine whether a strong translation reflects critical post-editing, independent human judgment, or unexamined reliance on machine output. Therefore, translation pedagogy should incorporate tasks that require students to document AI use, compare alternatives, justify revisions, and apply translation theory to specific textual problems. In this way, AI can be transformed from a black-box shortcut into a reflective learning resource that strengthens students' metacognitive awareness, cultural sensitivity, and professional identity as emerging literary translators.

ACKNOWLEDGMENT

The researcher wish to acknowledge the 18 undergraduate student translators from the Tadris Bahasa Inggris programme at STAIN Mandailing Natal who generously participated in this study and invested considerable time in completing the five-component translation tasks with careful attention to written strategy justification.

REFERENCES

Abdelhalim, S. M., Alsuhaibani, Z., & Alsahil, A. (2025). Empowering student translators: The impact of ChatGPT training on self-efficacy in literary translation. *SAGE Open, 15*(4). https://doi.org/10.1177/21582440251374800

Al Awdi, M. (2025). Equivalence in meaning: A comparative analysis of Nida's and Newmark's translation theories. *Educalitra: English Education, Linguistics, and Literature Journal, 4*(1), 86–103.

Alaa, A. M., & Al Sawi, I. (2023). *The analysis and quality assessment of translation*.

Aleedy, M., Alshihri, F., Meshoul, S., Al-Harthi, M., Alramlawi, S., Aldaihani, B., Shaiba, H., & Atwell, E. (2025). Designing AI-powered translation education tools: A framework for parallel sentence generation using SauLTC and LLMs. *PeerJ Computer Science, 11*, Article e2788. https://doi.org/10.7717/peerj-cs.2788

Baker, C. (2011). *Foundations of bilingual education and bilingualism* (5th ed.). Multilingual Matters.

Baker, M. (2018). *In other words: A coursebook on translation* (3rd ed.). Routledge. https://doi.org/10.4324/9781315619187

Beeby, A., Ensinger, D., & Presas, M. (2003). Building a translation competence model. In F. Alves (Ed.), *Triangulating translation: Perspectives in process-oriented research* (pp. 91–110). John Benjamins Publishing Company.

Belhassen, S., & Hamda, A. (2025). Translation students' reliance on and trust in artificial intelligence for successful translation projects: Opportunities, challenges, and implications. *Arab World English Journal for Translation & Literary Studies, 9*(2), 106–119.

Egdom, G. W., Declercq, C., & Kosters, O. (2024). Prompting ChatGPT to enhance literary MT output. In *Proceedings of the 1st Workshop on Creative-Text Translation and Technology* (pp. 15–25).

González Davies, M., & Scott-Tennent, C. (2005). A problem-solving and student-centred approach to the translation of cultural references. *Meta, 50*(1), 160–179. https://doi.org/10.7202/010666ar

Hajmalek, M. M., & Aghamohammadi, J. (2023). Applying task-based language teaching to translation instruction: Challenges and prospects. *Language Related Research, 13*(6), 99–129.

Hao, L., Tian, K., Salleh, U. K. M., Leng, C. H., Ge, S., & C., X. (2024). The effect of project-based learning and project-based flipped classroom on critical thinking and creativity for business English course at higher vocational colleges. *Malaysian Journal of Learning and Instruction, 21*.

Ibrahim, N. (2024). The use of artificial intelligence (AI) translation tools: Implications for tertiary students' language proficiency. *International Journal of Research and Innovation in Social Science, 8*(10). https://doi.org/10.47772/IJRISS

Kornacki, M. (2025). *Integrating generative AI into translator training: Challenges*.

Krings, H. P. (2001). *Repairing texts: Empirical investigations of machine translation processes*. Kent State University Press.

Lee, S. M. (2021). The effectiveness of machine translation in foreign language education: A systematic review and meta-analysis. *Computer Assisted Language Learning, 36*(1–2), 103–125. https://doi.org/10.1080/09588221.2021.1901745

Liu, K., & Afzaal, M. (2021). Artificial intelligence (AI) and translation teaching: A critical perspective on the transformation of education. *International Journal of Educational Sciences, 33*(1–3), 64–73. https://doi.org/10.31901/24566322.2021/33.1-3.1159

Naeem, M., Ssemugabi, S., & Yang, L. (2025). AI revolution in literary translation: A bibliometric review. *Journal of Innovation in Science, Technology and Management, 10*(40), 104–120. https://doi.org/10.35631/JISTM.1040008

Newmark, P. (1988). *A textbook of translation*. Prentice Hall.

Reyes Lozano, J., & Mejías-Climent, L. (2023). Beyond the black mirror effect: The impact of machine translation in the audiovisual translation environment. *Linguistica Antverpiensia, New Series: Themes in Translation Studies, 22*, 1–28.

Sohail, A., & Zhang, L. (2025). Using large language models to facilitate academic work in the psychological sciences. *Current Psychology, 44*(9), 7910–7918. https://doi.org/10.1007/s12144-025-07438-2

Strauss, A. M., & Corbin, J. M. (1998). *Basics of qualitative research: Techniques and procedures for developing grounded theory* (2nd ed.). SAGE Publications.

Venuti, L. (2017). *The translator's invisibility: A history of translation* (3rd ed.). Routledge.

Wang, J., & Fan, W. (2025). The effect of ChatGPT on students' learning performance, learning perception, and higher-order thinking: Insights from a meta-analysis. *Humanities and Social Sciences Communications, 7*. https://doi.org/10.1057/s41599-025-04787-y

Wutich, A., Beresford, M., & Bernard, H. R. (2024). *Sample sizes for 10 types of qualitative data analysis*. [Publication details needed].

Xiao, L., & Zeng, J. (2023). *An empirical study on the improvement of students' strategic competence*.

Zulkifli, M. F. (2025). AI revolution in literary translation: A bibliometric analysis. *Journal of Information System and Technology Management, 10*(40), 104–120. https://doi.org/10.35631/JISTM.1040008