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Toward a Cognitive Architecture of Human–AI Collaboration in AI-Assisted Translation

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Abstract:
The growing adoption of generative artificial intelligence (AI) in higher education has transformed translation from an individual cognitive activity into a collaborative process in which learners continuously interact with intelligent technologies. Although AI-assisted translation has received increasing scholarly attention, existing research has primarily focused on translation quality, technology acceptance, and ethical issues, offering limited understanding of the cognitive processes underlying human–AI collaboration during translation. This study investigates the cognitive architecture of AI-assisted translation by examining how cognitive work is distributed between learners and AI, how learners regulate AI-generated outputs, and how they reconstruct translations while maintaining human agency. A qualitative multiple case study was conducted with five undergraduate students enrolled in a *Translating General Text* course in the English Literature Study Program at Universitas Negeri Makassar, Indonesia. Data were collected through AI-assisted translation tasks, classroom observations, and semi-structured interviews and analyzed using reflexive thematic analysis. The findings reveal three interconnected cognitive dimensions. First, distributed cognitive processing enables AI to support lexical retrieval, semantic interpretation, and syntactic reformulation during translation. Second, metacognitive regulation allows learners to evaluate, accept, modify, reject, and regenerate AI-generated outputs according to contextual and semantic requirements. Third, human reconstruction demonstrates that learners integrate AI-generated suggestions with their own linguistic knowledge to produce coherent and contextually appropriate translations. Cross-case analysis further indicates that AI-assisted translation operates as a recursive human–AI cognitive system in which cognitive resources are shared while executive control remains with the learner. The study proposes an empirical cognitive architecture integrating distributed cognition and metacognitive regulation, extending current understandings of human–AI collaboration in translation education and providing pedagogical implications for fostering critical judgment, learner autonomy, and responsible AI integration.

Keywords: AI-Assisted Translation; Distributed Cognition; Higher Education; Metacognitive Monitoring; Qualitative Multiple Case Study

Introduction

The rapid advancement of generative artificial intelligence (AI) has fundamentally transformed teaching and learning practices in higher education, particularly in language-related disciplines where students increasingly interact with AI to support reading, writing, translation, and academic communication. Unlike earlier digital technologies that primarily provided access to information, generative AI actively participates in knowledge construction by producing linguistic outputs, explaining concepts, reformulating sentences, and responding dynamically to learners' prompts (Creely, 2024; Jung & Jin, 2025; Lee et al., 2023). These capabilities have shifted students' roles from solely generating language to continuously interacting with AI-generated content throughout the learning process. Consequently, learning is no longer understood as an exclusively internal cognitive activity but as a technology-mediated process in which cognitive work is increasingly shared between learners and intelligent systems. While this transformation creates opportunities for personalized learning and improved linguistic performance, it also raises important questions regarding how students maintain critical judgment, regulate AI-generated information, and preserve human agency during academic tasks (Chan et al., 2024; Li et al., 2025)

Translation represents one of the most cognitively demanding language activities because successful translation requires learners to comprehend source-text meaning, retrieve appropriate vocabulary, interpret contextual relationships, reorganize syntactic structures, and produce target texts that are both semantically accurate and culturally appropriate. Generative AI has become an increasingly common partner in this process by providing lexical suggestions, semantic explanations, sentence reformulations, and complete translation drafts within seconds. Previous studies have consistently demonstrated that AI can improve translation efficiency, linguistic fluency, and students' confidence while reducing the time required to complete translation tasks (Kwok et al., 2025; W. Wang & Lyu, 2025). Nevertheless, fluent AI-generated language does not necessarily guarantee semantic accuracy, contextual appropriateness, or cultural equivalence. Students frequently encounter situations in which AI produces grammatically acceptable yet contextually inappropriate or semantically inaccurate translations, requiring them to exercise critical judgment before incorporating AI suggestions into their own work. Accordingly, the educational value of AI-assisted translation should not be evaluated solely through translation quality or technological effectiveness, but also through the cognitive processes that emerge as learners interact with AI during translation.

Understanding these processes requires moving beyond traditional views of cognition as an activity occurring solely within the individual learner. Distributed Cognition Theory (Hutchins, 1995) argues that cognitive activity emerges through interactions among individuals, external representations, technological artifacts, and the surrounding environment. Within AI-assisted translation, generative AI functions as an external cognitive resource capable of supporting lexical retrieval, semantic interpretation, and syntactic reformulation, thereby extending learners' available cognitive resources during translation. However, distributed cognitive support alone cannot explain how students determine whether AI-generated translations are trustworthy or appropriate. This responsibility is explained by Metacognitive Monitoring (Nelson, 1990), which emphasizes learners' capacity to monitor their own cognitive performance, evaluate external information, regulate decision-making, and control subsequent actions. Rather than operating independently, distributed cognition and metacognitive monitoring interact continuously throughout AI-assisted translation.

Students first construct an initial understanding of the source text, consult AI when encountering linguistic difficulties, evaluate and regulate AI-generated suggestions, and subsequently reconstruct the translation according to their own linguistic knowledge, contextual understanding, and communicative intentions. The final translation therefore emerges not from AI alone nor from unaided human cognition, but from an iterative process of cognitive distribution, metacognitive regulation, and human reconstruction. Figure 1 synthesizes this conceptual architecture by illustrating how learners move dynamically from source-text comprehension to AI consultation, distributed cognitive processing, metacognitive evaluation, and translation reconstruction before producing the final target text.

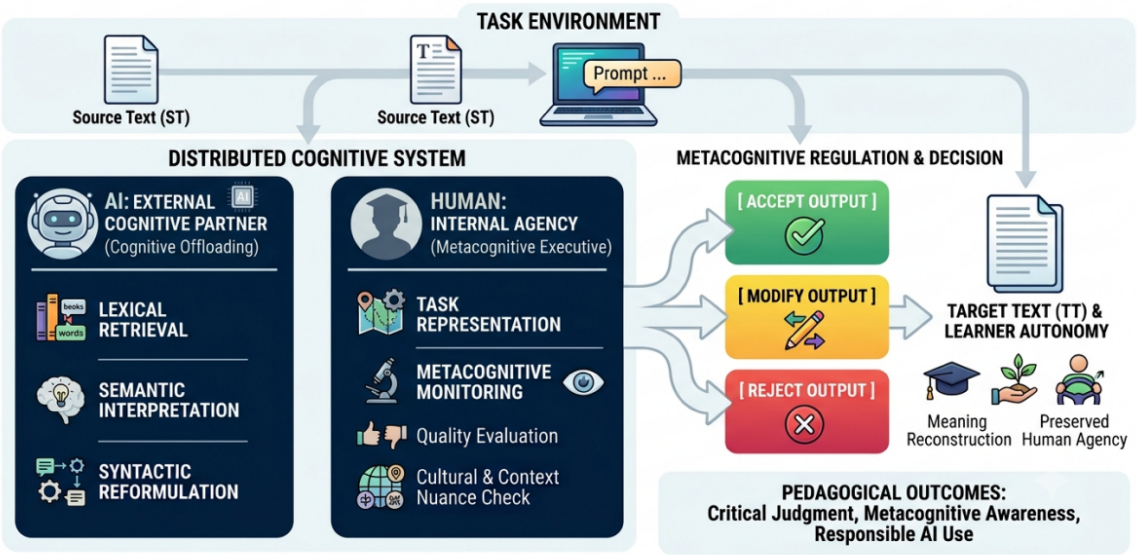


Figure 1. Human–AI Collaborative Translation Framework

Although research on generative AI in language education has expanded rapidly, existing studies have primarily examined technology acceptance, students' perceptions, ethical concerns, translation quality, writing performance, and learning outcomes (Belkina et al., 2025; Chan et al., 2024; Li et al., 2025). Comparatively little attention has been devoted to understanding the cognitive architecture underlying students' interactions with AI during authentic translation activities. In particular, previous studies rarely explain how cognitive work is distributed between learners and AI, how students regulate AI-generated outputs through metacognitive monitoring, or how they reconstruct AI-assisted translations while maintaining human agency. Consequently, the mechanisms through which external cognitive support and internal cognitive regulation operate together remain insufficiently understood, especially within EFL translation classrooms in higher education.

Addressing this gap, the present study investigates the cognitive architecture of AI-assisted translation among undergraduate students enrolled in the Translating General Text course in the English Literature Study Program at Universitas Negeri Makassar, Indonesia. Employing a qualitative multiple case study design involving five information-rich participants, the study explores how students distribute cognitive work between themselves and generative AI, regulate AI-generated outputs through metacognitive monitoring, and reconstruct translations through human judgment and decision-making. By integrating Distributed Cognition Theory with Metacognitive Monitoring, this study proposes a theoretically grounded explanation of AI-assisted translation as a collaborative cognitive system rather than a technology-driven translation process. The findings are

expected to contribute to the emerging literature on AI-enhanced language learning by extending current understandings of human–AI collaboration while providing practical implications for translation pedagogy that promotes critical thinking, learner autonomy, and responsible AI integration in higher education.

Accordingly, this study addresses the following research questions:

1. How is cognitive work distributed between students and generative AI during translation?
2. How do students monitor and regulate AI-generated translation outputs throughout the translation process?
3. How do students reconstruct AI-generated translations through human agency and decision-making?

Method

Research Design

This study employed a qualitative multiple case study design to investigate the cognitive architecture underlying students' AI-assisted translation processes. A multiple case study was considered appropriate because it enables an in-depth exploration of complex cognitive phenomena within authentic educational settings while facilitating cross-case comparisons to identify recurring patterns and individual variations (Stake & Schwandt, 2006; Yin, 2018). Rather than evaluating the effectiveness of AI-generated translations, the study sought to understand how students distributed cognitive activities between themselves and generative AI and how they exercised metacognitive monitoring throughout the translation process. Each participant represented an individual case, allowing the researchers to examine the dynamic interaction between human cognition and artificial intelligence during authentic translation tasks.

Research Context and Participants

The study was conducted in the *Translating General Text* course offered by the English Literature Study Program, Faculty of Languages and Literature, Universitas Negeri Makassar, Indonesia. The course introduces undergraduate students to the principles and practice of translating general English texts into Indonesian, emphasizing lexical accuracy, semantic equivalence, grammatical appropriateness, and contextual adaptation.

Five undergraduate students participated in this study. Participants were selected through purposive sampling because qualitative multiple case study research seeks information-rich cases that can provide detailed insights into the phenomenon under investigation (Patton, 2014). To be eligible, participants were required to meet four inclusion criteria: (1) they were enrolled in the *Translating General Text* course during the data collection period; (2) they had prior experience using generative AI tools, particularly ChatGPT, to support translation activities; (3) they were willing to participate in classroom observations, AI-assisted translation tasks, and semi-structured interviews; and (4) they were able to reflect on and explain their cognitive decision-making during AI-assisted translation. The five participants represented individual cases for in-depth analysis, allowing the researchers to examine both common cognitive patterns and individual variations across cases. To protect confidentiality, participants were assigned pseudonyms (P1–P5) throughout the study.

Data Collection

Data were collected using three complementary instruments to capture students' cognitive activities from multiple perspectives.

AI-Assisted Translation Task

Participants completed an authentic classroom translation task in which they translated an English general text into Indonesian using generative AI as an available

learning partner. They were free to consult AI throughout the translation process while retaining full responsibility for producing the final translation. The completed translations served as the primary source for examining how students interacted with AI, negotiated linguistic choices, and reconstructed translated texts.

Classroom Observation

Non-participant classroom observations were conducted throughout the translation activity. The researcher documented observable behaviors associated with cognitive engagement, including hesitation before consulting AI, repeated prompting, comparison between AI-generated and self-produced translations, independent revisions, rereading behaviors, deletion or modification of AI suggestions, and other visible decision-making activities. Field notes were recorded systematically to contextualize students' interactions with AI during the translation process.

Semi-Structured Interviews

Following the completion of the translation task, each participant participated in an individual semi-structured interview lasting approximately 30–45 minutes. The interviews were designed as retrospective reflections on participants' translation decisions rather than evaluations of AI itself. Participants were asked to explain why they consulted AI, how they interpreted AI-generated suggestions, how they evaluated translation quality, and how they decided to accept, modify, reject, or regenerate AI outputs. They also reflected on how they balanced AI assistance with their own linguistic knowledge when producing the final translation. All interviews were audio-recorded and transcribed verbatim.

Data Analysis

The data were analyzed using Reflexive Thematic Analysis (Braun & Clarke, 2021). Analysis began with repeated reading of the three data sources—the completed translation products, classroom observation notes, and interview transcripts—to achieve familiarity with each participant's translation process. The researchers first conducted within-case analysis by examining each participant individually to identify meaningful cognitive activities occurring throughout AI-assisted translation. Initial inductive codes were generated from participants' observable actions, translated texts, and interview accounts without imposing predetermined theoretical categories. Examples of these initial codes included *requesting lexical alternatives*, *seeking semantic clarification*, *reformulating AI-generated sentences*, *comparing AI output with the source text*, *rejecting inaccurate suggestions*, *revising prompts*, and *reconstructing translated texts*.

Subsequently, related codes were grouped into broader categories through iterative comparison across the five cases. These categories were continuously refined until three overarching themes emerged that collectively described the cognitive architecture of AI-assisted translation. After the inductive themes had been established, the researchers conducted cross-case analysis to identify common cognitive patterns as well as individual variations among participants. Finally, the emergent themes were interpreted through the complementary theoretical lenses of Distributed Cognition Theory (Hutchins, 1995) and Metacognitive Monitoring (Nelson, 1990). These theories were employed during interpretation rather than theme generation to explain how cognitive work was distributed between learners and AI, how learners regulated AI-generated outputs, and how human agency was maintained throughout translation reconstruction.

Trustworthiness

Trustworthiness was established using the criteria of credibility, dependability, confirmability, and transferability (Guba & Lincoln, 1994). Credibility was enhanced through methodological triangulation by integrating evidence from participants'

completed translation products, classroom observations, and semi-structured interviews. Rather than relying on a single source of evidence, emerging interpretations were continuously compared across the three datasets to ensure that each theme was supported by converging evidence. Dependability was strengthened through maintaining a detailed audit trail documenting coding decisions, category refinement, and theme development throughout the analytical process. Confirmability was enhanced through iterative researcher discussions and reflexive memo writing to minimize subjective interpretation during coding and analysis. Transferability was facilitated by providing rich descriptions of the research context, participant characteristics, data collection procedures, and analytical processes, enabling readers to determine the applicability of the findings to comparable educational contexts.

Ethical Considerations

Prior to data collection, all participants received detailed information regarding the purpose of the study and voluntarily provided informed consent. Participants were informed that their involvement was entirely voluntary and that they could withdraw from the study at any stage without academic consequences. To protect confidentiality, pseudonyms were assigned to all participants, and identifying information was removed from transcripts and research records. The collected data were securely stored and used exclusively for academic research purposes.

Results and Discussion

Results

Analysis of the AI-assisted translation tasks, classroom observations, and semi-structured interviews revealed three interconnected patterns in the five participants' translation processes: AI-supported cognitive distribution, metacognitive regulation of AI output, and human reconstruction of the target text. Although the participants differed in their level of linguistic proficiency, confidence, and reliance on AI, they generally followed a similar process. They first attempted to understand the source text independently, consulted AI when encountering linguistic or contextual difficulties, evaluated the generated suggestions, and revised the output before producing the final translation. The findings therefore indicate that AI-assisted translation was neither fully independent nor fully automated. Instead, it emerged as a negotiated process in which cognitive work was distributed between the students and AI while final decisions remained under human control.

AI-Supported Distribution of Cognitive Work

The first theme concerns how participants distributed parts of the translation process to AI. Classroom observations showed that the participants generally began by reading the source text independently. They underlined unfamiliar words, reread difficult sentences, and attempted to infer meaning from the surrounding context. AI consultation usually occurred after participants recognized that their own linguistic resources were insufficient to resolve a particular problem. In this sense, AI was not always the first source of translation but became an external resource when students experienced lexical, semantic, syntactic, or contextual uncertainty.

Across the five cases, AI was most consistently used for lexical retrieval, semantic clarification, and syntactic reformulation. Some participants also consulted AI to identify more natural Indonesian expressions or to clarify culturally specific meanings.

Table 1. Distribution of AI-Supported Cognitive Activities across Participants

AI-supported cognitive activity	P1	P2	P3	P4	P5
Retrieving unfamiliar vocabulary	✓	✓	✓	✓	✓

Clarifying contextual meaning	✓	✓	✓	✓	✓
Explaining complex sentences	✓	✓	✓	✓	✓
Reformulating sentence structure	✓	✓	✓	✓	✓
Suggesting natural Indonesian expressions	✓	✓	✓	✓	✓
Clarifying cultural references	✓	–	✓	✓	–
Generating a complete initial translation	–	✓	–	✓	✓

Lexical retrieval represented the most immediate form of cognitive distribution. All participants used AI when they could not recall an appropriate Indonesian equivalent or when a word had several possible meanings. However, participants did not always request a direct translation. Some asked AI to explain the meaning of a word within the sentence before selecting an equivalent.

> P1 explained: "I usually read the sentence first and tried to understand it. When I found a word that had several meanings, I asked AI which meaning was suitable for that context."
>
> P3 described a similar strategy: "Sometimes I knew the general meaning of the word, but I was not sure whether it was formal, informal, or suitable for the sentence. AI helped me see the alternatives."
>
> P5 emphasized that AI was particularly useful when dictionary meanings were insufficient: "A dictionary gives several meanings, but it does not always tell me which one is natural in the paragraph. I asked ChatGPT to explain the word based on the whole sentence."

Observation data supported these comments. P1 and P3 frequently highlighted individual words before opening the AI interface. They then compared several suggested equivalents and returned to the source text before inserting one into their translation. This behavior indicates that lexical retrieval was externalized to AI, but lexical selection remained an active human decision.

Semantic interpretation constituted a second form of distributed cognitive activity. Participants used AI to explain long sentences, implicit meanings, and relationships between ideas. Rather than simply asking AI to translate the entire text, several participants requested explanations in simpler language.

> P2 stated: "There were sentences that I could translate word by word, but I still did not understand the actual message. I asked AI to explain the sentence first, and after that I translated it."
>
> P4 similarly commented: "The difficult part was not always the vocabulary. Sometimes I understood every word, but I did not understand what the writer wanted to say."
>
> P3 added: "I asked AI to separate the sentence into smaller parts because the original sentence was too long. After I understood each part, I combined the meaning again in Indonesian."

During observation, P3 entered a prompt asking AI to "explain the sentence in simple English" rather than requesting an immediate Indonesian translation. P3 then produced a translation independently based on the explanation. This episode demonstrates that AI sometimes functioned as an interpretive intermediary rather than as the direct producer of the target text.

Syntactic reformulation was also evident across all five cases. Participants consulted AI when the grammatical structure of the source text could not be transferred naturally into Indonesian. AI offered alternative arrangements, but students usually selected or combined these alternatives.

P1 explained: "The English sentence was very long. If I followed the same structure, the Indonesian version became confusing. AI gave me another structure, but I still changed it."

P4 reported: "I used AI to see how the sentence could be reorganized. I did not use the whole answer, but it gave me an idea about where to place the main information."

P5 stated: "AI helped me break one complex sentence into two sentences. That made the translation more natural, although I changed some words afterward."

The observation notes showed that P4 and P5 repeatedly moved between the source sentence, AI output, and their own draft. They did not simply transfer the generated sentence. Instead, they treated the AI response as an external representation that could be examined and reorganized. Therefore, the first theme suggests that AI expanded the participants' available cognitive resources by supporting lexical search, semantic interpretation, and sentence reformulation. Nevertheless, the distribution of cognitive work did not eliminate student involvement. The participants remained responsible for deciding when AI assistance was needed and how its contributions should be incorporated.

Metacognitive Regulation of AI-Generated Output

The second theme concerns the participants' monitoring and regulation of AI-generated translations. Although AI produced grammatically fluent responses, all five participants reported that fluency alone was not sufficient to establish accuracy. They evaluated the outputs by comparing them with the source text, considering contextual meaning, examining naturalness in Indonesian, and determining whether the suggestions preserved the writer's intended message.

Three major decisions emerged from the data: accepting, modifying, and rejecting AI output. Acceptance usually occurred when the suggested translation was considered accurate, clear, and contextually appropriate. Modification occurred when an output was partially useful but required lexical, grammatical, or contextual adjustment. Rejection occurred when the output distorted meaning, sounded unnatural, or failed to represent the source text adequately.

Table 2. Metacognitive Decisions Identified across the Five Cases

Metacognitive decision	P1	P2	P3	P4	P5
Accepting an AI suggestion without major revision	✓	✓	✓	✓	✓
Modifying lexical choices	✓	✓	✓	✓	✓
Restructuring AI-generated sentences	✓	✓	✓	✓	✓
Rejecting inaccurate suggestions	✓	✓	✓	✓	✓
Requesting alternative outputs	✓	✓	✓	✓	✓
Verifying meaning against the source text	✓	✓	✓	✓	✓
Checking naturalness in Indonesian	✓	✓	✓	✓	✓

Participants frequently described a difference between linguistic fluency and semantic accuracy. P1 explained: "Sometimes the sentence looked very good in Indonesian, but when I checked it again, the meaning was slightly different from the original."

P2 similarly noted: "AI can make the translation sound smooth, but smooth does not always mean correct. I still had to compare it with the English text."

P4 stated: "There were outputs that were grammatically correct, but the emphasis changed. The important idea in the source text became less clear."

These comments were reflected in observed behavior. P1 repeatedly reread the source sentence after receiving an AI-generated translation. In one episode, the participant deleted an initially accepted output after recognizing that the AI had generalized a more specific term. P4 also rejected a fluent translation because it altered the relationship between two clauses.

Participants additionally monitored cultural and contextual appropriateness. This was particularly evident when literal translations sounded unusual or inappropriate in Indonesian.

> P3 explained: "AI translated the phrase literally, but Indonesian readers would not normally say it that way. I changed it into an expression that had the same function."
>
> P4 commented: "The meaning was technically correct, but the expression sounded like machine language. I tried to make it sound more natural for Indonesian readers."
>
> P1 added: "I considered who would read the translation. Some words suggested by AI were too formal for the text, so I replaced them."

Observation notes showed that P3 paused for an extended period after receiving an AI translation of an idiomatic expression. The participant then asked AI for an explanation of the phrase, searched for an equivalent expression, and finally produced a different Indonesian version. This sequence illustrates that the participant did not evaluate the output solely at the word level but also considered communicative function.

The participants also regulated AI interaction by reformulating prompts. When the first response was unsatisfactory, they added contextual information, requested alternatives, or specified the preferred translation style.

> P5 stated: "If I only wrote 'translate this,' the answer was sometimes too general. I had to explain the context and ask for a natural Indonesian version."
>
> P2 explained: "I changed the prompt when the output was too literal. I asked AI to keep the meaning but make the sentence easier to understand."
>
> P4 reported: "Sometimes I asked for three alternatives because I did not want to depend on only one answer."

These iterative prompts indicate that metacognitive regulation did not occur only after AI generated a response. It also shaped the interaction itself. Participants monitored the quality of previous responses and adjusted their instructions to obtain more relevant assistance.

The depth of monitoring varied among the cases. P1 and P3 demonstrated extensive comparison between source and target texts and frequently rejected generated suggestions. P2 and P5 tended to accept more of the initial output but still revised expressions they considered unnatural. P4 relied heavily on AI for initial formulation but conducted substantial revision afterward. Thus, metacognitive regulation was present in all cases, although its intensity and form differed.

Overall, this theme demonstrates that AI-generated output did not directly determine the final translation. The participants exercised metacognitive control by judging accuracy, checking contextual compatibility, and deciding whether to accept, modify, or reject each contribution. Metacognitive monitoring therefore functioned as the central mechanism that regulated the distribution of cognitive work between the students and AI.

Human Reconstruction of the Target Text

The third theme concerns the reconstruction of AI-supported translations into final texts. Following AI consultation and evaluation, participants reorganized linguistic material according to their own understanding of the source text and their expectations of natural Indonesian expression. Reconstruction involved more than correcting isolated

errors. It included substituting vocabulary, restructuring sentences, clarifying relationships between ideas, adapting expressions, and restoring meanings that had been weakened or altered by AI.

Table 3. Human Reconstruction Activities across Participants

Reconstruction activity	P1	P2	P3	P4	P5
Replacing AI-selected vocabulary	✓	✓	✓	✓	✓
Reorganizing sentence structure	✓	✓	✓	✓	✓
Combining human and AI alternatives	✓	✓	✓	✓	✓
Correcting semantic shifts	✓	✓	✓	✓	✓
Adapting cultural or contextual meaning	✓	–	✓	✓	✓
Improving cohesion across sentences	✓	✓	✓	✓	✓
Preserving personal translation choices	✓	✓	✓	✓	✓

All participants emphasized that they did not view the AI output as a completed translation. P2 explained: "I treated the AI answer as a draft. It helped me start, but I still had to make it suitable for the text."

P1 similarly stated: "AI gave me several possibilities, but the final sentence was my decision. I combined some words from AI with my own translation."

P3 described reconstruction as a process of restoring meaning: "Sometimes the AI version lost a small detail. I added it again because I thought that detail was important in the original text."

P4 emphasized the importance of naturalness: "I rewrote many sentences because they sounded translated. I wanted the target text to sound as if it was originally written in Indonesian."

P5 stated: "Even when I used most of the AI version, I changed the order of information and some expressions so that the paragraph was easier to understand."

The translation products provided visible evidence of these reconstruction processes. Comparisons between the AI-generated suggestions and the final texts showed that all participants made changes. P1 frequently replaced general vocabulary with more context-specific terms. P2 retained several AI-generated sentence structures but simplified complex expressions. P3 made the most extensive semantic revisions, particularly when the AI output omitted implied meanings. P4 reorganized long sentences and adjusted formal expressions. P5 focused on readability by dividing complex sentences and adding cohesive connections.

Reconstruction also involved combining several sources of knowledge. Participants integrated their initial interpretation, AI suggestions, contextual understanding, and knowledge of Indonesian language conventions.

P1 explained: "Sometimes my first translation was closer to the meaning, but AI's sentence was more natural. I combined both versions."

P3 stated: "I compared my own interpretation with the AI explanation. When they were different, I went back to the source text and decided which one was more logical."

P5 commented: "AI helped with the structure, but I used my own words for the final version because I understood the topic better after reading everything."

These accounts show that reconstruction did not simply consist of editing machine errors. It represented a synthesis of internal and external cognitive resources. The final

translations emerged from interaction among the source text, the participants' linguistic knowledge, AI-generated alternatives, and ongoing metacognitive judgments.

The participants also associated reconstruction with personal responsibility. Although they acknowledged the efficiency of AI, they believed that the final text should reflect their own decisions.

> P2 stated: "I could not submit the AI translation directly because I was still responsible for whether the meaning was correct."
>
> P4 explained: "AI can suggest, but it does not know exactly what I want to emphasize. I had to make the final decision."
>
> P3 added: "When I changed the output, I felt that the translation became mine, not only the AI's answer."

This sense of ownership was visible in the classroom observations. Before submission, all participants conducted a final reading of the target text. They made additional changes even after AI interaction had ended, including punctuation correction, vocabulary replacement, and sentence reorganization. No participant submitted an unchanged AI-generated translation. Human reconstruction therefore served as the final stage through which participants re-established control over meaning, language, and translation quality.

Cross-Case Comparison

Cross-case analysis revealed a shared cognitive pattern across the five participants, but it also identified differences in the degree of AI reliance and metacognitive engagement.

Table 4. Cross-Case Patterns in AI-Assisted Translation

Participant	Primary use of AI	Level of AI reliance	Monitoring intensity	Dominant final action
P1	Lexical and contextual clarification	Moderate	High	Context-sensitive revision
P2	Initial translation and sentence simplification	High	Moderate	Selective modification
P3	Semantic explanation and cultural interpretation	Moderate	High	Extensive meaning reconstruction
P4	Complete translation and syntactic reformulation	High	High	Structural rewriting
P5	Vocabulary, fluency, and readability support	High	Moderate	Readability-oriented revision

P1 and P3 initially relied more heavily on their own interpretation and used AI selectively to address specific problems. Their interview responses and observed behavior showed intensive source-text comparison and frequent rejection of unsuitable suggestions. P2, P4, and P5 used AI earlier and more extensively, particularly for generating initial translations. However, higher AI reliance did not necessarily result in passive acceptance. P4, for example, generated complete translations through AI but then performed substantial restructuring and contextual adaptation.

The most important variation across cases concerned the relationship between AI reliance and metacognitive monitoring. Participants with strong monitoring practices

were able to use AI extensively while retaining control over the final translation. By contrast, participants with less intensive monitoring accepted more generated language and focused primarily on fluency and readability. Nevertheless, even these participants revised the outputs before submission.

Across all cases, the translation process was recursive rather than strictly linear. Participants frequently moved back from evaluation to AI consultation, revised prompts, reconsidered the source text, and reconstructed their translation multiple times. A typical process involved reading the source text, identifying a difficulty, consulting AI, evaluating the response, modifying or rejecting it, and returning to AI when further clarification was needed. Therefore, the findings indicate that AI-assisted translation functioned as a cyclical human–AI interaction rather than a single transfer of translation responsibility.

Taken together, the findings show that the cognitive architecture of AI-assisted translation consisted of three mutually dependent dimensions. First, AI extended the participants' cognitive resources by supporting lexical retrieval, semantic interpretation, and syntactic reformulation. Second, metacognitive monitoring regulated whether those resources were trusted, modified, or rejected. Third, human reconstruction transformed the distributed contributions into a final target text that reflected the participants' linguistic judgment and contextual understanding. The final translation was therefore produced neither by the student alone nor by AI independently, but through a distributed cognitive process governed by human evaluation and decision-making.

Discussion

The findings demonstrate that AI-assisted translation is better understood as a distributed cognitive system than as a technology-assisted linguistic activity. Rather than functioning merely as an external translation tool, generative AI became an active cognitive partner that participated in lexical retrieval, semantic interpretation, and syntactic reformulation throughout the translation process. However, these distributed cognitive functions did not diminish learners' responsibility for constructing meaning. Instead, participants continuously coordinated their own linguistic knowledge with AI-generated information, suggesting that cognitive activity emerged through interactions among the learner, the source text, AI, and the evolving target text. This finding extends Hutchins' (1995) Distributed Cognition Theory by illustrating that contemporary generative AI is not simply an external artifact supporting cognition but an adaptive conversational agent capable of dynamically responding to learners' cognitive needs. Unlike traditional translation tools or dictionaries that primarily provide static linguistic resources, generative AI contributed to multiple cognitive operations simultaneously, including vocabulary retrieval, contextual explanation, structural reformulation, and alternative meaning construction. The present findings therefore suggest that distributed cognition within AI-assisted translation operates through continuous negotiation between internal cognitive resources and externally generated linguistic representations rather than through a simple transfer of cognitive work to technology.

Importantly, the findings also indicate that cognitive distribution alone was insufficient to produce successful translations. Across all five participants, AI-generated outputs were rarely accepted without evaluation. Instead, students repeatedly compared generated translations with the source text, examined semantic accuracy, assessed contextual appropriateness, reformulated prompts, and requested alternative responses before making translation decisions. These behaviors highlight the central role of metacognitive monitoring in regulating interactions between learners and AI. Consistent with Nelson and Narens' (1990) model, participants continuously monitored the quality of AI-generated information and exercised cognitive control by accepting, modifying,

rejecting, or regenerating translations. However, the present findings extend conventional understandings of metacognitive monitoring because learners were not regulating only their own cognitive performance but also evaluating the performance of an external intelligent system. This suggests that AI-assisted learning introduces an additional regulatory dimension in which metacognitive monitoring is directed simultaneously toward internal comprehension and external AI-generated knowledge. Consequently, effective AI use depends not on the sophistication of the technology itself but on learners' capacity to critically evaluate, regulate, and strategically employ AI-generated information throughout task completion.

A particularly important contribution of this study concerns the reconstruction stage that emerged consistently across all participants. Although AI frequently generated complete translations or linguistically fluent alternatives, participants rarely treated these outputs as final products. Instead, they reconstructed the translations by replacing lexical items, reorganizing sentence structures, restoring omitted meanings, adapting cultural expressions, and integrating their own contextual understanding. This reconstruction process demonstrates that human agency remained central despite extensive AI support. Rather than functioning as passive recipients of machine-generated language, learners acted as final meaning-makers who synthesized internal knowledge with external suggestions to produce coherent target texts. Previous studies have commonly evaluated AI-assisted translation in terms of translation quality, linguistic accuracy, or learning efficiency (Kwok et al., 2025; Q. Wang, 2025), whereas the present findings reveal that reconstruction itself constitutes a distinct cognitive process through which learners reclaim ownership of AI-supported language production. Human agency therefore resides not in avoiding AI but in maintaining authority over the interpretation, adaptation, and final realization of meaning.

Taken together, the three findings reveal a coherent cognitive architecture of AI-assisted translation. The translation process progressed through three interconnected stages: distributed cognitive processing, metacognitive regulation, and human reconstruction. Rather than occurring sequentially in a rigid manner, these stages interacted recursively as participants moved repeatedly between source-text interpretation, AI consultation, evaluation, prompt revision, and translation reconstruction. Learners frequently returned to earlier stages whenever AI-generated responses failed to satisfy semantic or contextual expectations, indicating that AI-assisted translation is characterized by iterative cognitive cycles rather than linear task execution. This recursive architecture expands current conceptualizations of human–AI collaboration by demonstrating that generative AI supports cognition without replacing the learner's executive control. AI contributes linguistic possibilities, whereas learners retain responsibility for evaluating evidence, resolving ambiguity, integrating contextual knowledge, and determining the final translation outcome.

These findings also carry important pedagogical implications for translation education in higher education. As generative AI becomes increasingly accessible, translation instruction should move beyond encouraging or discouraging AI use toward developing students' capacity to collaborate critically with intelligent systems (Bozkurt et al., 2024; Guo & Lin, 2025). Students require explicit instruction not only in effective prompting strategies but also in evaluating semantic fidelity, recognizing contextual inconsistencies, detecting cultural mismatches, and reconstructing AI-generated language according to communicative purposes. Consequently, translation competence in the era of generative AI should be conceptualized not merely as bilingual linguistic proficiency but also as the ability to regulate distributed cognitive resources while preserving human agency throughout the translation process. Developing these competencies will enable

students to use AI as an intellectual partner rather than as a substitute for independent judgment.

Finally, this study contributes theoretically by integrating Distributed Cognition Theory and Metacognitive Monitoring into a unified explanation of AI-assisted translation. Previous studies have generally applied these perspectives independently, with distributed cognition explaining technological mediation and metacognition explaining learner regulation. The present findings demonstrate that these perspectives are mutually complementary within AI-supported learning environments. Distributed cognition explains 'where' cognitive work is shared, whereas metacognitive monitoring explains 'how' learners maintain control over that distributed cognitive system. Their integration provides a more comprehensive account of AI-assisted translation by explaining both the distribution of cognitive resources and the mechanisms through which human agency is preserved. The resulting cognitive architecture offers a theoretical framework that may also inform future investigations of AI-supported writing, reading, language learning, and other technology-mediated academic practices beyond translation.

Conclusion

This study investigated the cognitive architecture of AI-assisted translation among undergraduate EFL students by examining how cognitive work was distributed between learners and generative AI, how students regulated AI-generated outputs, and how they reconstructed translations through human agency. The findings revealed that AI-assisted translation is not a process of technological substitution but a collaborative cognitive activity in which learners and AI perform complementary roles. AI primarily functioned as an external cognitive partner by supporting lexical retrieval, semantic interpretation, and syntactic reformulation, whereas students retained responsibility for evaluating, regulating, and integrating AI-generated information into the final translation. The translation process therefore emerged through three interconnected cognitive dimensions: distributed cognitive processing, metacognitive regulation, and human reconstruction. Together, these dimensions constitute a recursive cognitive architecture in which learners continuously move between source-text interpretation, AI consultation, evaluation, revision, and reconstruction before producing the target text.

The study also contributes theoretically by demonstrating that Distributed Cognition Theory and Metacognitive Monitoring provide complementary perspectives for explaining human–AI collaboration in translation. Distributed cognition explains how cognitive resources are shared between learners and AI, whereas metacognitive monitoring explains how learners preserve executive control over those distributed resources through continuous evaluation and decision-making. Their integration offers a more comprehensive understanding of AI-assisted translation as a collaborative cognitive system in which human agency remains central despite extensive technological support. Rather than diminishing learners' cognitive engagement, generative AI reshapes cognitive activity by redistributing specific linguistic operations while preserving human responsibility for meaning construction and translation quality.

From a pedagogical perspective, the findings suggest that translation education should move beyond teaching students how to use AI tools efficiently toward developing their capacity to collaborate critically with AI. Translation competence in the era of generative AI requires not only linguistic proficiency but also the ability to evaluate AI-generated information, identify semantic and contextual inaccuracies, regulate technological assistance, and reconstruct translations according to communicative purposes. Accordingly, AI literacy should be integrated into translation instruction as a

component of critical thinking, metacognitive awareness, and responsible decision-making rather than as a purely technological skill.

This study is limited by its small sample of five undergraduate students from a single translation course within one Indonesian university. Consequently, the findings are intended to provide analytical rather than statistical generalization, and the proposed cognitive architecture should be interpreted within this educational context. Future research may examine larger and more diverse learner populations, compare novice and experienced translators, investigate different generative AI platforms, or incorporate additional data sources such as screen recordings, eye-tracking, keystroke logging, or think-aloud protocols to capture the dynamic development of cognitive processes during AI-assisted translation. Longitudinal studies are also needed to examine how sustained interaction with generative AI influences learners' cognitive development, translation expertise, and metacognitive regulation over time.

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