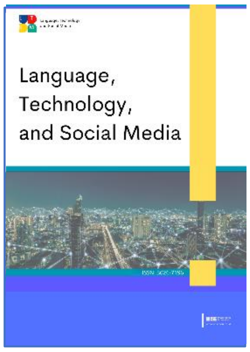

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Research Article

Reflective Regulation of AI-Assisted Translation: Longitudinal Development of Technology Competence and Critical AI Literacy in an Indonesian EFL Classroom

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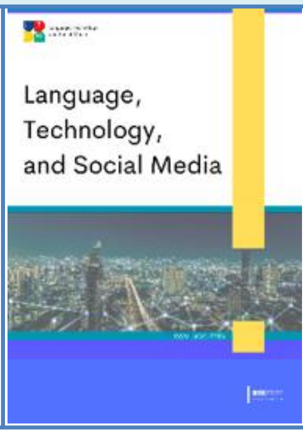
Abstract

Artificial intelligence (AI) is now routinely used in translation education, but frequent use does not demonstrate critical or professionally responsible technology competence. This study examined how 20 undergraduate EFL translation students regulated AI assistance during a one-semester course. A qualitative-dominant embedded mixed-methods design followed six Indonesian-to-English translation phases structured by Assessment-as-Learning and repeated Plan–Monitor–Evaluate reflection. The dataset comprised 120 reflective journals, phase-based Likert responses used only as descriptive corroboration, and participant-observation notes. Longitudinal thematic analysis began with inductive coding and then interpreted cross-phase patterns through the European Master's in Translation Technology Competence framework and metacognitive regulation. In Phase 1, 11 students articulated no AI-use plan, six offered vague plans, and three described relatively explicit plans; AI was used mainly for post-draft correction. In Phases 2–3, students increasingly compared, modified, or rejected suggestions according to meaning, grammatical accuracy, academic register, and contextual fit. In Phases 4–6, reflections more consistently defined human authorship and accountability and positioned AI as a verification resource rather than a primary text generator. The trajectory was cohort-dominant rather than uniform, and the design does not establish that reflection alone caused the change. The findings conceptualize technology competence as the reflective regulation of language-mediated human–AI interaction and identify structured metacognitive reflection as a plausible way to develop critical AI literacy in translation education.

Keywords: AI-Assisted Translation; Critical AI Literacy; EFL Translation; Machine Translation Literacy; Metacognition; Technology Competence.



INTRODUCTION

Artificial intelligence has become a routine part of contemporary translation practice. Neural machine translation and generative AI can propose lexical choices, reformulate sentences, compare alternatives, and generate drafts. These capabilities redistribute some translation decisions between students and systems [1], [2], [3]. In translator education, the central problem is how students decide when assistance is useful, when it distorts meaning or register, and when convenience displaces the interpretive responsibility of professional language work [4], [5].

Recent translation research increasingly treats human–AI collaboration as a competence problem rather than a simple performance comparison. Studies of AI-assisted post-editing show that technology can reduce effort or support terminology work, yet outputs still require context-sensitive revision and independent judgment [6], [7]. Work on AI-assisted translation education likewise reports cognitive, motivational, and identity effects that depend on how technology is pedagogically framed [8]. Ethical questions are equally important: students' judgments about AI-assisted language work involve ownership, fairness, learning, and accountability, not merely whether a tool is technically accurate [9]. These findings make it insufficient to equate frequent AI use with advanced digital competence.

The distinction is especially important in English-as-a-foreign-language translation classrooms. When students translate from Indonesian into English, they must coordinate source-text meaning, target-language accuracy, academic register, audience expectations, and pragmatic fit. AI can scaffold these linguistic decisions, but its fluent output can also be treated as an authority without adequate evaluation. The educational problem concerns how students regulate AI assistance while preserving translator agency and responsibility for the final text.

This study addresses that question through the European Master's in Translation (EMT) concept of Technology Competence, understood here as the strategic, critical, responsible, and ethically aware use of technological resources in translation practice [47]. Although the EMT framework was developed for European translator education, its emphasis on professional decision-making offers an analytically useful lens for an Indonesian undergraduate EFL setting when applied cautiously rather than as a context-free benchmark. The framework is used as an interpretive lens; the analysis does not assume that European curricular conditions transfer directly to this setting.

A second conceptual anchor is Assessment-as-Learning (AaL). AaL differs from ordinary reflective journaling because reflection is not appended to instruction as a retrospective narrative; it is used to regulate subsequent action. In this study, repeated Plan–Monitor–Evaluate (PME) cycles required students to anticipate a translation strategy, attend to decisions while translating, and evaluate both their output and their use of AI. This design makes metacognition observable through students' articulated planning, monitoring, evaluation, justification, and regulation of technology-mediated choices.

The empirical gap is longitudinal. Much of the existing literature examines translation quality, post-editing effort, attitudes, or single-task performance. Less is known about how students' technology-related reasoning changes over a sustained sequence of translation tasks, how reflective regulation relates to those changes, and where ethical boundaries emerge or remain absent. The gap is particularly visible in EFL settings in which AI functions simultaneously as linguistic support and a potential source of dependency.

This study asks: What longitudinal patterns of change in strategic AI use, metacognitive regulation, and ethically framed technology competence emerge across six phases of an AI-mediated reflective translation course? It traces how students moved from reactive correction toward more selective and accountable human–AI interaction and examines reflective regulation as a mechanism through which operational tool use may develop into critical AI literacy. The analysis distinguishes authorship-oriented awareness from broader issues such as bias, privacy, transparency, and disclosure. It therefore treats AI as a mediator of linguistic decision-making rather than merely as an educational instrument.

LITERATURE REVIEW

Machine Translation Literacy and Technology Competence

Machine translation literacy has been defined as knowledge of how MT works, when it is useful, and what consequences follow from its use [10]. For education, that definition shifts attention from operating a system to interrogating its output and its place in a workflow. Bowker similarly argues that non-specialist and professional users require explicit literacy instruction because fluent machine output can conceal limitations that only informed users recognize [11]. Translator trainers have consequently been urged to assume a literacy-consultant role that makes technological affordances, risks, and professional consequences visible to learners [12].

This literacy perspective is compatible with research that repositions the human translator as an agent who adds value through judgment rather than as a competitor to automation [13]. Student use studies also show that learners often negotiate a tension between developmental goals and immediate expedience when using MT [14]. Perception research among translation instructors and learners further indicates that familiarity with MT does not eliminate concerns about competence, pedagogy, or professional sustainability [15]. AI-supported translation may improve accuracy or motivation in some conditions, but such benefits are mediated by task design and learner behavior [16].

Pedagogical evidence therefore supports explicit instruction rather than laissez-faire exposure. Translation-app use can affect performance, but effects depend on how learners integrate the tools into translation processes [17]. Students who are asked to interrogate Google Translate output can develop greater awareness of errors and revision strategies [18], while surveys of neural MT use consistently show that learners appreciate efficiency but remain uncertain about reliability and appropriate dependence [19]. Process studies reinforce this distinction: student post-editing of neural MT does not automatically reach professional quality [20], and post-editing can reduce effort while still requiring substantial revision competence [21]. Dedicated guidelines and training are therefore necessary because novice post-editors do not necessarily interpret professional expectations consistently [22].

Competence also requires measurement choices that distinguish translation, revision, and post-editing rather than collapsing them into one technological skill [23]. Training experiments in public-service translation show that explicit MT and post-editing modules can support digital adaptation, but students still require curricular integration and reflective engagement [24]. Systematic reviews of MT-assisted language learning similarly find pedagogical benefits alongside risks of overreliance and uneven learning outcomes [25], [26].

Generative AI, Human Agency, and Ethical Regulation

Generative AI intensifies earlier MT-literacy questions because it can explain, rewrite, evaluate, and generate target-language text in conversational form. Higher-education research shows that students recognize efficiency and individualized support but also identify accuracy, dependency, authorship, and integrity concerns [27]. A systematic review of GPT in translation similarly concludes that prompting conditions and task design materially affect translation performance, making uncritical reliance pedagogically untenable [28]. Academic-integrity research cautions that framing generative AI only as a cheating problem is also inadequate, because educational responses must distinguish prohibited substitution from legitimate learning support [29].

Translation-specific studies reveal similarly mixed positions. Students often value ChatGPT for speed and linguistic suggestions while remaining concerned about cultural accuracy and overdependence [30]. Professional translators' responses range from pragmatic adoption to resistance, and later evidence on trust shows that acceptance is shaped by perceived control, transparency, and professional identity rather than technological capability alone [31], [32]. Post-editing studies also show that trainees can misjudge task difficulty and their own performance, which makes metacognitive monitoring central to competent AI use [33]. Generative AI can augment post-editing across domains, but the value of assistance depends on purposeful verification rather than wholesale acceptance [34].

Taken together, the literature suggests a progression that is theoretically plausible but not automatically linear: operational access can support strategic use; strategic use can become reflective regulation; and reflective regulation can create conditions for ethically responsible human–AI collaboration. The present study examines whether such a pattern is visible longitudinally in students' own reflections and classroom behavior. It does not assume that every learner follows the same path or that authorship awareness constitutes comprehensive ethical AI literacy.

METHODS

Research Design and Setting

The study used a qualitative-dominant embedded mixed-methods design within a longitudinal classroom inquiry. Qualitative reflections and observation field notes constituted the primary evidential base; Likert responses embedded in the reflection sheets were secondary, descriptive data used to corroborate or complicate qualitative interpretation rather than to test hypotheses. This design was appropriate because the research question concerned change in students' reasoning and technology-use practices over time rather than population-level effect estimation.

The study was conducted across one academic semester in a Translation for General Purpose course in the English Education Study Program at Universitas Negeri Gorontalo, Indonesia. Students completed six Indonesian-to-English academic translation tasks. The course sequence was progressively challenging, but the available records contain no task-level word counts, standardized difficulty indices, or common external quality benchmark. The analysis therefore does not attribute the observed changes to task equivalence or increasing difficulty.

Research Participants

Participants were all 20 fifth-semester students enrolled in the course. All had completed prerequisite courses in translation theory and practice. The available study records contain no standardized English-proficiency scores, baseline translation test, age distribution, or prior-AI-use inventory. The analysis therefore makes no claim of baseline equivalence beyond shared enrolment and prerequisite coursework.

Pedagogical Intervention

Across six phases, each translation task was followed by a structured PME reflection cycle. Planning prompts elicited intended translation strategies and anticipated use of AI; monitoring prompts elicited when AI was consulted, how strategies changed, and how outputs were compared; evaluation prompts elicited judgments about translation quality, limitations of AI output, reasons for accepting, modifying, or rejecting suggestions, and implications for future work. Phases 1–5 also included structured class discussion, while Phase 6 concluded with a plenary synthesis discussion on AI use, translator agency, and professional responsibility. Classroom discussion functioned as part of the pedagogical intervention and contextual interpretation; it was not coded as a separate primary dataset. Table 1 summarizes the documented sequence.

Table 1. Documented structure of the six-phase intervention

Phase	Translation activity	Reflective cycle	Classroom activity	Analytical emphasis
1	Indonesian→English academic translation	Plan–Monitor–Evaluate	Structured discussion	Baseline patterns of AI use and explicit planning
2	Indonesian→English academic translation	Plan–Monitor–Evaluate	Structured discussion	Purposeful comparison and strategy adjustment
3	Indonesian→English academic translation	Plan–Monitor–Evaluate	Structured discussion	Selective acceptance, modification, and rejection
4	Indonesian→English academic translation	Plan–Monitor–Evaluate	Structured discussion	Emergence of explicit authorship/accountability boundaries
5	Indonesian→English academic translation	Plan–Monitor–Evaluate	Structured discussion	Negotiated principles of human–AI collaboration
6	Indonesian→English academic translation	Plan–Monitor–Evaluate	Plenary synthesis	Meta-strategic monitoring and reflective responsibility

Data Sources and Collection

The primary corpus comprised 120 reflective journals (20 students × 6 phases). Each journal contained open-ended PME prompts and embedded Likert items. The qualitative entries documented strategies, reasons for consulting AI, translation problems, evaluations of AI-generated alternatives, and planned improvements. Participant observations were conducted throughout the semester; field notes recorded interaction with AI tools, peer exchanges, discussion themes, and contextual behavior relevant to interpreting the journals. The records repeatedly identify ChatGPT and DeepL as tools used by students, but the study did not experimentally standardize one system, version, or prompt protocol.

All 120 journal entries were available for qualitative analysis. Item-level denominators were unavailable for several early-phase Likert percentages. Values such as 46.2% and 76.9% could not be converted into defensible participant counts without reconstructing missing metadata and were therefore excluded as stand-alone evidence. Quantitative responses are used only as descriptive corroboration where their interpretation is unambiguous, separating the qualitative longitudinal evidence from incomplete survey metadata.

Data Analysis and Trustworthiness

Reflective journals and observation notes were analyzed using theoretically informed longitudinal thematic analysis. The analytic logic follows reflexive thematic analysis in moving iteratively between familiarization, coding, category development, and interpretation [35]. Metacognition was conceptualized as monitoring and regulation of cognition [36], while self-regulation was understood as learners' cyclical management of goals, strategies, monitoring, and evaluation [37], [38]. Translation-research methodological guidance informed the integration of process-oriented qualitative evidence with descriptive quantitative support [39], [40].

Analysis proceeded in four stages. First, reflections and observation notes were open-coded with descriptive labels grounded in participants' reported practices, including 'AI as dictionary,' 'comparing AI outputs,' 'verifying AI suggestions,' 'rejecting AI output,' 'setting AI boundaries,' and 'balancing human and AI contributions.' Second, related codes were clustered into categories representing recurring forms of AI use, reflective behavior, and decision-making. Third, categories were compared across phases to identify continuity, change, exceptions, and early or delayed emergence. Fourth, the longitudinal patterns were interpreted in relation to EMT Technology Competence, AaL, and PME. The theoretical frameworks were therefore used after inductive coding rather than imposed as a priori codebooks.

Coding decisions were reviewed iteratively and discussed through peer debriefing with an experienced qualitative researcher. Trustworthiness was further supported by triangulation between journals and classroom observations, longitudinal comparison across phases, an audit trail of key analytic decisions, and use of excerpts that represented both dominant patterns and temporal variation. The analysis does not claim inter-rater reliability because the study records do not document independent duplicate coding or a coefficient; peer debriefing is reported only for the role it actually performed.

RESULTS AND DISCUSSION

Results

The data support an analytic trajectory from instrumental to strategic and then more explicitly ethical-reflective technology use, but not a uniform stage model in which every student changed at the same time. Phase boundaries summarize dominant cohort patterns. Traces of later reasoning appeared earlier for some students, particularly in Phase 3, and the observational evidence shows variation in how quickly students became willing to question AI output. Table 2 summarizes the empirical anchors and interpretive limits of this trajectory.

Table 2. Empirical anchors for the longitudinal trajectory

Analytic period	Dominant pattern	Empirical anchors	Interpretive boundary
Phase 1: Instrumental	AI mainly used after drafting for correction	20 journals; 11 no explicit AI-use plan, 6 vague plans, 3 relatively explicit plans; observations recorded whole-text consultation and limited scrutiny	Frequent use did not equal strategic competence
Phases 2–3: Strategic	Comparison, verification, modification, and selective rejection	40 journals; reflections increasingly cited accuracy, naturalness, academic register, and contextual fit; observations showed side-by-side comparison and peer evaluation	Change was cohort-dominant, not identical for every student
Phases 4–6: Ethical-reflective	AI regulated as secondary verification/refinement resource	60 journals; four recurring principles: human authorship, no direct uncritical adoption, AI as secondary tool, personal accountability; independent drafting became more visible in observations	Ethical reasoning centered on authorship/accountability, not full AI-governance literacy

Phase 1: Instrumental Use and Reactive Proofreading

Phase 1 served as a diagnostic baseline. Across all 20 journals, AI was typically described as something consulted after an initial draft to correct grammar, spelling, vocabulary, or lexical equivalence. Explicit planning was limited: 11 students did not articulate when or how AI would be used, six made only general references to consulting AI, and three described a relatively explicit plan. Even the more explicit plans did not state criteria for deciding whether AI suggestions should be accepted, revised, or rejected.

Monitoring was similarly reactive. Students rarely described comparing multiple alternatives or changing strategy while translating. Evaluations tended to label AI as 'helpful' or the translation as needing ‘improvement’ without explaining the basis for a decision. Observations supported this pattern: students commonly pasted a completed text into ChatGPT or DeepL and accepted revisions with limited scrutiny. One reflection stated, ‘I do not really have a strategy, I just translate word for word and then use AI to check it’ (P1, Phase 1). This phase therefore indicates operational familiarity without corresponding evidence of critical regulation.

Phases 2–3: Strategic and Selective Collaboration

Across the 40 journals from Phases 2 and 3, planning became more explicit and task-oriented. Students increasingly described examining the source text, anticipating terminology or register problems, and deciding in advance when technological assistance would be useful. Monitoring shifted from correction to comparison: students juxtaposed AI-generated alternatives with their own translations and evaluated whether suggestions fit meaning, academic style, audience, and communicative purpose.

The change was especially visible in the reasons students gave for revising. Rather than treating the AI output as authoritative, they increasingly modified or rejected suggestions. One student wrote, ‘I changed my initial literal translation after comparing it with AI’s suggestion for a more natural academic phrase, but the final choice was mine’ (P3, Phase 3). Another noted that AI was useful for grammar and forgotten vocabulary but ‘not always suitable for academic style’ and therefore still required revision (P6, Phase 3). Classroom observations likewise recorded more side-by-side comparison and peer discussion of accuracy, naturalness, register, and contextual fit. These practices represent strategic regulation rather than mere increases in tool use.

Phases 4–6: Authorship, Accountability, and Reflective Regulation

The 60 journals from Phases 4–6 show the clearest emergence of explicitly ethical language. Four recurring principles organized students’ later reflections: maintaining human authorship, rejecting direct adoption of AI-generated text without critical revision, positioning AI as a secondary verification or refinement tool, and retaining personal accountability for the final translation. The pattern developed progressively: Phase 4 made boundaries more explicit, Phase 5 contained personally negotiated principles of acceptable collaboration, and Phase 6 more often framed AI as a resource for testing or strengthening an independently formed judgment.

Participant language illustrates the shift. P19 wrote in Phase 4, ‘I make a manual draft first so that AI does not become the author. AI is only used to check minor grammar issues or suggest alternative diction.’ P6 had already articulated an earlier version of this boundary in Phase 3: ‘AI is a tool, not a writer.’ Several later reflections used a ‘70% human–30% AI’ formulation. In the revised interpretation, this ratio is treated only as a student-generated metaphor for preserving human responsibility, not as an objective ethical standard or a recommended allocation of work.

The ethical scope also remained limited. Students’ reflections centered on authorship, plagiarism concerns, and accountability; they did not consistently address algorithmic bias, privacy, data governance, model transparency, or disclosure. It would therefore overstate the evidence to claim comprehensive ethical AI literacy. The more defensible conclusion is that the intervention coincided with a stronger authorship- and accountability-oriented form of critical AI literacy.

Discussion

The longitudinal evidence supports a distinction between exposure and competence. Students were already using AI in Phase 1, yet their reasoning was mainly corrective and post hoc. This finding is consistent with machine-translation literacy research showing that competent use depends on understanding limitations, purposes, and consequences rather than simply having access to a system [10], [11]. It also converges with post-editing research in which novice translators benefit from machine output while still struggling to identify subtle errors or apply professional criteria [20], [21], [22], [23].

The principal theoretical contribution concerns the role of metacognitive regulation. The observed shift from 'use AI to correct' toward planning when to consult it, monitoring dependence on it, and evaluating its suggestions suggests a mechanism that links technology competence with critical AI literacy. This does not mean that reflection alone caused the trajectory. Task familiarity, instructor feedback, classroom discussion, repeated translation practice, and increasing comfort with the course may also have contributed. The design cannot disentangle these influences. What the data do show is that the PME routine repeatedly required students to externalize decisions that would otherwise remain tacit, making technology use available for scrutiny and revision.

This interpretation extends contemporary work on translator agency. Collaborative-learning experiments have shown that students can reposition themselves as human decision-makers in machine-mediated workflows [13], while studies of generative AI in translator training report changes in identity and cognition when technological assistance is deliberately scaffolded [8]. The present findings add a process account: agency became visible not through rejection of AI but through increasingly conditional acceptance of it. Students demonstrated agency when they could explain why a suggestion was suitable, modify it to fit context, or reject it despite surface fluency.

The results also qualify optimistic accounts of AI-supported translation. Generative AI can provide rapid feedback and support data-driven learning [5], and AI-assisted post-editing can alter effort profiles [6]. However, benefits are pedagogically meaningful only when students retain interpretive responsibility. This point is especially relevant for Indonesian EFL students translating into English, where fluent AI output may mask pragmatic, register, or cultural mismatches. Indonesian evidence on post-editing and AI-enabled MT similarly suggests that students value technological assistance while still requiring explicit critical guidance [41], [42].

Finally, the findings refine the meaning of 'ethical' competence. The students' strongest ethical language concerned who remains the author and who is accountable for the final text. This is important but narrower than comprehensive AI ethics. Studies of AI-assisted academic language work show that fairness and learning concerns can extend well beyond plagiarism [9], and current AI discussions also foreground privacy, bias, transparency, and disclosure. Accordingly, the Ethical-Reflective label in this article denotes an empirically bounded form of ethical awareness, not mastery of the full governance landscape.

For pedagogy, the implication is practical: AI should be integrated through explicit decision points. Translation tasks can require students to state an initial strategy before opening an AI tool, identify the linguistic or contextual problem that motivates consultation, compare outputs against independent criteria, document rejected suggestions, and close with a responsibility statement explaining what remains the translator's decision. This structure preserves the benefits of language technology while making human judgment an assessable learning outcome.

Recent research further supports treating technology competence as a pedagogically developed capacity rather than a by-product of tool exposure. Studies of translation educators foreground metacognition as a driver of technology competence [43], direct comparisons of AI and student translation demonstrate that apparent fluency does not eliminate quality differences requiring human judgment [44], self-reflection research in GenAI-supported assessment shows that structured reflection can make ethical tool use more transparent [45], and AI-supported evaluation research demonstrates the value of combining quantitative and qualitative evidence rather than relying on automated scores alone [46].

CONCLUSION

Across a six-phase reflective translation course, students' dominant AI-use practices changed from reactive proofreading toward more strategic comparison, selective modification, and explicit regulation of authorship and accountability. Competence became visible in students' ability to plan consultation, monitor dependence, test suggestions against linguistic and contextual criteria, and justify final decisions. The findings conceptualize technology competence as reflective regulation of language-mediated human–AI interaction. Metacognitive regulation offers a plausible pedagogical bridge between operational tool use and critical AI literacy, although the design cannot establish causality. The pedagogical implication is to assess the reasoning surrounding AI use, not only the linguistic quality of the final translation. The conclusions should nevertheless be read within the limits of one 20-student Indonesian EFL cohort, one semester, non-standardized task sequences, incomplete item-level metadata for several embedded Likert responses, and the absence of an independent performance-based translation-quality outcome. Future research should test the proposed mechanism across institutions and language directions, combine process evidence with blinded product assessment, and examine whether reflective regulation persists after instructional scaffolding is removed.

LIMITATIONS

This study is bounded by a single institutional context and a small intact class, so the trajectory should be treated as an analytically transferable pattern rather than statistically generalizable evidence. No standardized baseline proficiency measure, AI-familiarity inventory, or common task-difficulty index was available. The course sequence also makes alternative explanations—including task familiarity, teacher feedback, peer dialogue, and general maturation—plausible. Several early-phase Likert percentages lacked recoverable item-level denominators in the archived manuscript materials; these values were therefore excluded from primary evidential claims rather than reconstructed. The study also did not include an independent translation-quality test, so it documents changes in reflective technology use, not verified gains in translation performance. Finally, the ethical dimension that emerged was mainly authorship- and accountability-oriented, and the rapid evolution of AI systems limits direct transfer of tool-specific practices to future platforms.

AUTHOR INFORMATION

Corresponding Authors
Sri Widyarti Ali – Universitas Negeri Gorontalo (Indonesia);
orcid.org/0009-0000-0690-114X
Email: widyartiaaali@ung.ac.id

Authors
Sri Widyarti Ali – Universitas Negeri Gorontalo (Indonesia);
orcid.org/0009-0000-0690-114X
Karmila Machmud – Universitas Negeri Gorontalo (Indonesia);
orcid.org/0000-0001-8618-3482
Novriyanto Napu – Universitas Negeri Gorontalo (Indonesia);
orcid.org/0000-0002-4663-7854
Suleman Bouti – Universitas Negeri Gorontalo (Indonesia);
orcid.org/0009-0002-3593-9379

AUTHOR CONTRIBUTION

S.W.A. designed the research framework, formulated the research objectives, developed the methodology, and prepared the original draft. K.M., N.N., and S.B. contributed to research-design supervision, theoretical refinement, validation of the qualitative analysis, and interpretation of the longitudinal themes. They also supported classroom implementation, participant observation, research documentation, and manuscript revision. S.W.A. coordinated the overall research process and finalized the manuscript for publication. All authors reviewed and approved the final version of the manuscript.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DECLARATION OF USE OF AI IN SCIENTIFIC WRITING

The author(s) used ChatGPT by OpenAI during the preparation of this work to assist in language refinement, grammar correction, academic paraphrasing, manuscript structuring, and translation of several sections into academic English. After utilizing the tool/service, the author(s) thoroughly reviewed, revised, and edited the content as necessary and assumed full responsibility for the publication's content.

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