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Analysis of AI integration strategies of engineering students in ESL composition

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Abstract

The study examined how 100 engineering students from Civil, Mechanical, Electrical, and Electronics Engineering programs integrated artificial intelligence (AI) tools into their English academic writing during the second semester of Academic Year 2025–2026. Using a sequential explanatory mixed-methods design, the researcher first measured AI literacy with a validated 15-item Likert-scale instrument, which showed that students had a moderate level of AI literacy across three domains: understanding, application, and ethics. In the qualitative phase, 10 purposively selected students with lower AI literacy scores and more problematic AI integration patterns participated in semi-structured group interviews, and the data were analyzed using Braun and Clarke's thematic analysis. Four major themes emerged: Academic Survival, Cognitive Scaffolding, Strategic Humanization, and Ethical Paradox, showing how students used AI under time pressure, for language support, to preserve human authorship, and while negotiating ethical tensions. Their AI-supported writing strategies aligned with Zimmerman's three self-regulated learning phases of forethought, performance, and self-reflection. Quantitative analysis indicated no statistically significant relationship between students' AI literacy levels and the complexity of their AI integration strategies. Triangulated findings led to the development of the AI Writing Handbook for Future Engineers, designed to promote transparent, human-centered AI use and address ESL engineering writing, disclosure, and equity issues in AI access.

Keywords: artificial intelligence literacy, AI integration strategies, English second language writing, engineering students, self-regulated learning

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1. Introduction

The rapid integration of artificial intelligence into higher education reshapes what it means for students to be literate, especially in English-medium academic tasks. For engineering students who write in English as a second language, AI tools now intersect with existing writing strategies and self-regulation practices, creating new opportunities and risks for learning. To situate this study, the introduction first examines literacy and AI in higher education, then explores ESL writing strategies among engineering students, and finally considers self-regulated learning and the ethical use of AI as a guiding framework.

Literacy and AI in Higher Education - Literacy and learning in higher education are changing rapidly as artificial intelligence (AI) becomes part of everyday academic work. Students in many disciplines, including engineering, now rely on AI tools to search for information, generate ideas, draft paragraphs, and revise their writing for assignments and projects (Ajjawi et al., 2024; Sullivan et al., 2023). Instead of working only with print texts and human feedback, they interact with systems such as ChatGPT, Grammarly, and QuillBot, as well as AI features embedded in learning platforms (Perkins, 2023). In this context, literacy no longer refers only to reading and writing in the traditional sense; it also includes the capacity to understand, manage, and critically evaluate AI-mediated information and feedback during academic study (Chan, 2023; Chen, 2025).

AI literacy has therefore emerged as a key 21st-century competence that combines technical, critical, and ethical dimensions. It involves basic knowledge of how AI systems operate, practical skills in using them for specific tasks, and the ability to question, verify, and ethically evaluate their outputs. Recent work in higher education suggests that students' AI literacy is uneven: many can operate tools confidently but show limited awareness of algorithmic limitations, cultural and linguistic bias, and ethical risks around plagiarism and authorship (Chen, 2025; Perkins, 2023; Sullivan et al., 2023). Conceptually, AI literacy aligns with learner-centered and constructivist perspectives, which view students as active decision-makers who choose tools and strategies to support their learning rather than simply accepting whatever AI produces (Chan, 2023). At the same time, AI use in higher education is increasingly shaped by institutional frameworks such as academic integrity codes, responsible technology use guidelines, and data privacy policies, which attempt to define acceptable AI-assisted work in assessments (Bearman & Ajjawi, 2023; Perkins & Roe, 2023).

Within this landscape, there is growing interest in how AI literacy develops in specific disciplines and student groups. Surveys and case studies show that students in STEM and engineering programs frequently integrate AI into coursework but do so in ways that are not always visible to instructors or aligned with formal policies (Ajjawi et al., 2024; Cotton et al., 2024; Sullivan et al., 2023). Much of the existing literature reports general levels of AI knowledge, attitudes, or ethical concerns at the institutional or national level, but it often pays less attention to how particular groups, such as ESL engineering students, use AI in discipline-specific writing tasks or negotiate institutional rules in concrete situations (Chen, 2025; Lee et al., 2025). This gap highlights the need for research that connects AI literacy with actual writing practices, self-regulation, and ethical decision-making in engineering programs.

ESL Writing Strategies among Engineering Students - In English as a Second Language (ESL) contexts, academic writing is a complex, multi-stage process that involves planning, drafting, revising, and reflecting, rather than simply producing grammatically correct sentences (Braun & Clarke, 2006, 2021). Students are expected to organize ideas coherently, construct logical arguments, and engage with sources in ways that fit the expectations of academic communities. For engineering students, these demands are visible in laboratory reports, project proposals, design documentation, and research papers that require both technical accuracy and clear written communication (Generative AI in Academic Writing: Exploring ESL Students' Strategies, 2025; Influence of

GenAI on Higher Education ESL Students' Writing, 2025). Writing in English becomes a point where disciplinary knowledge, language proficiency, and genre awareness intersect, and difficulties in any of these areas can affect academic performance.

Empirical studies on ESL engineering students report persistent challenges in lexical choice, syntactic accuracy, cohesion, and maintaining coherent arguments across longer texts (Generative AI in Academic Writing: Exploring ESL Students' Strategies, 2025; Locating the Intersection of Generative Artificial Intelligence and Human English Writing Skills, 2024). Learners often struggle to use precise technical terms, articulate procedures and results clearly, and adapt their writing to specialized genres such as experimental reports or feasibility studies (Lee et al., 2025). These difficulties are frequently linked to limited exposure to strong disciplinary models, restricted time for intensive writing practice due to heavy technical workloads, and limited individualized feedback, factors that can lead students to view writing as stressful and burdensome (Influence of GenAI on Higher Education ESL Students' Writing, 2025). In response, many resort to coping strategies such as reusing templates, focusing only on sentence-level corrections, or prioritizing task completion over thorough revision.

At the same time, research on successful ESL writers highlights a broader set of strategies that support development: global planning, outlining, multiple drafting, seeking feedback from peers and instructors, and revising at the level of structure and argument, not just grammar (Braun & Clarke, 2006, 2021). In recent years, technology-mediated strategies have become more visible. Studies show that ESL undergraduates increasingly use online corpora, digital dictionaries, and generative AI tools during different phases of writing to check expressions, explore discipline-specific phrasing, and receive immediate feedback on grammar and cohesion (Lee et al., 2025; Generative AI Is Useful for Second Language Writing, 2025). However, many of these studies either focus on traditional strategies or treat technology use in general terms; they rarely provide detailed accounts of how AI tools are integrated into the planning, drafting, and revising stages of ESL composition specifically for engineering students (Generative AI in Academic Writing: Exploring ESL Students' Strategies, 2025; Influence of GenAI on Higher Education ESL Students' Writing, 2025). This lack of fine-grained description makes it difficult for instructors to design writing tasks and policies that make constructive use of AI while still strengthening students' independent writing skills.

Self-Regulated Learning and Ethical Use of AI - Self-regulated learning (SRL) offers a useful lens for understanding how students manage complex tasks such as academic writing. SRL describes learners who set goals, plan their work, monitor progress, and evaluate outcomes across three interconnected phases: forethought, performance, and self-reflection (Zimmerman, 2000). In writing, self-regulated learners decide what they want their text to accomplish, choose strategies for generating and organizing ideas, track their progress during drafting, and revise in response to feedback and self-assessment. Metacognitive awareness is the ability to think about one's own thinking and learning is central to this process, especially in ESL academic writing where students must integrate content knowledge, language skills, and critical engagement with sources.

The introduction of AI tools into learning environments intensifies the importance of SRL. Recent studies suggest that AI systems can support SRL by providing feedback, recommending strategies, and prompting reflection, but they also warn that benefits depend on how students regulate their AI use (Self-Regulated Learning with AI: A Comparative Analysis of General and Discipline-Specific Tools, 2025). Some learners use AI tools to clarify concepts, check understanding, and reflect on their progress, while others primarily rely on AI to complete tasks more quickly or to bypass challenging aspects of writing (Generative AI in Academic Writing: Exploring ESL Students' Strategies, 2025; Influence of GenAI on Higher Education ESL Students' Writing, 2025). In writing contexts, this distinction is crucial: the same tool can either scaffold deeper learning or encourage over-reliance, depending on the level of metacognitive control the student maintains.

Ethical awareness is closely intertwined with SRL in AI-mediated academic work. Students using AI to support writing must make decisions about authorship, originality, transparency, and responsible use of AI-generated content. Recent discussions on generative AI in higher education stress the need for clear institutional guidance so that students know what constitutes acceptable assistance and what crosses into academic misconduct (Perkins, 2023; Perkins & Roe, 2023; Ajjawi et al., 2024). These discussions emphasize academic honesty, respect for intellectual labor, and human-centered uses of AI that augment, rather than replace, human judgment and creativity (Bearman & Ajjawi, 2023; Ethical Use of Generative AI in Engineering, 2024). For ESL engineering students, these ethical and metacognitive dimensions are particularly salient: they often work under heavy technical workloads while being expected to produce polished English texts, conditions that can intensify the temptation to over-rely on AI or to hide AI involvement (Cotton et al., 2024; Sullivan et al., 2023).

Despite increasing attention to AI, SRL, and ethics, much of the current literature addresses general student populations or broad course contexts rather than ESL academic writing in engineering programs (Sullivan et al., 2023; ChatGPT in Engineering Education: Revolutionizing Writing, 2025). There is still limited descriptive evidence on how engineering students regulate their AI use at the planning, drafting, and revising stages of ESL writing, how they interpret and negotiate institutional policies on AI assistance, and how their AI literacy levels shape these decisions (Ajjawi et al., 2024; Chen, 2025). This gap creates a mismatch between high-level institutional guidelines and the realities of classroom practice. Addressing this gap is essential for designing pedagogical frameworks and institutional supports such as the AHCD framework and the *AI Writing Handbook for Future Engineers* that promote AI-enhanced, ethically grounded, self-regulated writing.

Objectives - This study analyzed AI integration strategies of engineering students in ESL composition. Specifically, it aims to (1) determine the AI literacy level of engineering students; (2) determine the AI integration strategies in the three phases of the writing process and (3) proposed AI Writing Handbook for Future Engineers.

2. Methodology

This section describes the research methods which were used to study how engineering students use AI for their ESL writing together with their writing methods and their perspectives. The research focused on the student's perspective as the main focus while it maintained structured methods for data collection and analysis.

Research Design - This study used a sequential explanatory mixed-methods research design to serve as the primary strategic guideline in the study. The methodology will be organized into two components which include the quantitative descriptive-survey phase that will establish AI literacy and self-regulated writing levels of engineering students and the qualitative phenomenological phase that will investigate the details of these experiences. The research includes both methods because they enable the researcher to use numerical data to create an explanation which connects statistical information with actual life experiences and academic challenges and the Ethical Paradox. Two separate components of the AHCD Framework provide the research base which establishes its statistical foundation while meeting the actual requirements of ESL classrooms.

Source of Data - For the quantitative phase, the study uses stratified random sampling to select 100 engineering students from four programs: Civil Engineering (CE), Mechanical Engineering (ME), Electrical Engineering (EE), and Electronics Engineering (ECE). The population is first divided into strata by program, and then 25 students are randomly selected from each stratum. Stratified sampling is appropriate when the population has distinct subgroups that must be represented proportionally or equally, and it improves precision and subgroup representation compared with a simple random sample of the same size (Cochran, 1977; Lohr, 2021; Saunders, Lewis, & Thornhill, 2019). In this study, equal allocation across the four programs ensures balanced representation of each engineering field and supports comparison across strata (Kish, 1965; Sharma, 2017).

The choice of 100 respondents is justified because it provides a manageable yet adequate quantitative sample for descriptive analysis in a four-stratum design, especially when the goal is to compare group patterns rather than estimate a population parameter with high precision. In applied educational research, sample size is often determined by feasibility, access, and the need for stable descriptive results, while maintaining coverage of all relevant subgroups (Creswell & Creswell, 2018; Lohr, 2021). The study uses a balanced design of 25 respondents per program to ensure equal representation and workable data collection.

Ten (10) students who obtain comparatively lower AI literacy scores and report more limited or problematic AI integration strategies across the writing phases are selected for in-depth, semi-structured interviews. This purposive sampling strategy is appropriate when the researcher seeks information-rich participants who can provide detailed insights into a phenomenon under study (Patton, 2015; Creswell & Creswell, 2018). Selecting students with lower scores is especially useful because their experiences can reveal the barriers, misconceptions, and support needs that the AI Writing Handbook for Future Engineers should address.

Research Ethics - The research was conducted in accordance with established principles of research ethics, with the well-being, privacy, and rights of all 100 participants as the central concern throughout the process. Before collecting any data, an informed consent procedure was carried out in a detailed and transparent manner to ensure that students fully understood the purpose of the study, the activities they would be asked to engage in, any potential risks, and their right to withdraw at any time without penalty. Consent forms clearly stated that participation was voluntary and that refusal or withdrawal would not affect their academic standing or relationships with instructors.

To protect the identity of the 10 selected interview participants, each was assigned a unique code like Participant 1, Participant 2, and so on. This coding system ensured confidentiality and maintained the anonymity of all interview data, even when rich, detailed narratives were reported. In discussing sensitive topics such as the use of AI in writing and related ethical dilemmas, the application of coded labels prevented any direct linkage of responses to individual students, thereby creating a safer, non-punitive environment in which participants could speak honestly and openly. All data both digital and physical were stored in encrypted and password-protected files accessible only to the researcher. Digital records such survey responses, audio recordings, and interview transcripts were kept on secure devices, while printed consent forms and any handwritten notes were stored in a locked space. The research aims to foster an open, reflective discussion on academic integrity and AI-assisted writing by treating participants with dignity, maintaining a non-judgmental stance, and upholding strict ethical safeguards. These practices were designed to protect participants, build trust, and ultimately contribute to a more informed and responsible academic culture within the university community.

Research Instrument - Two main instruments were used in the study to collect credible and meaningful data. The first is the AI Literacy and Writing Self-Regulation Scale, a Likert-type survey adopted from existing frameworks on AI literacy and self-regulated learning. The AI literacy component is grounded in recent AI literacy scales that conceptualize AI literacy as a cluster of knowledge, skills, and ethical dispositions related to understanding, evaluating, and using AI tools responsibly in learning contexts. The self-regulation component is conceptually drawn from the Self-Regulated Learning (SRL) framework originally proposed by Zimmerman (2000), which structures learning into three phases: forethought for planning and goal-setting, performance for strategy use and monitoring, and reflection for self-evaluation and adaptive regulation. The scale in this study adopts and recontextualizes these ideas for the specific context of engineering students writing in English as a second language with AI support. It consists of 16 items distributed across the three SRL-related phases: forethought, where items capture how students think about AI before writing (e.g., planning when and how to use AI and setting goals and ethical boundaries); performance, where items describe how students employ AI during the writing process, including tool selection, draft management, and monitoring AI-generated text; and reflection, where items focus on how students revise and evaluate their work after AI feedback, compare AI-suggested text to their own thinking, and decide what to keep, discard, or modify. All items use a Likert-type format a 5-point scale from strongly disagree to strongly agree, allowing the study to quantify students' self-reported tendencies across AI literacy-related and self-regulation-related behaviors. A reliability test using Cronbach's alpha yielded a value of 0.87, indicating that the scale is internally consistent and reliable for measuring AI-related self-regulation in this context. In addition, the survey includes background questions and items that implicitly categorize participants into levels of AI literacy, which the study interprets qualitatively as low for basic operational skill only, limited critical and ethical awareness, moderate for some understanding of AI capabilities and limitations, with emerging but inconsistent self-regulation, and high for critical, ethical, and self-regulated use of AI integrated thoughtfully into the writing process.

The second instrument is a semi-structured group-interview guide developed by the researcher for the qualitative phase, framed as a group interview. The guide is organized around the three phases of the writing process: planning, drafting, and reflection and its questions are sequenced to first build rapport, then gradually move into more specific, reflective territory: introductory questions explore participants' background and general experience with AI tools; planning-phase questions investigate how students decide whether, when, and which AI tools to use before writing and what they expect from AI; drafting-phase questions examine how students use AI while composing, including idea generation, structure, and negotiation between their own thinking and AI suggestions; and reflection-phase questions focus on how students review AI-generated text, revise heavily or minimally, and evaluate the final product in terms of authenticity and authorship. The guide contains 16 key questions, some of which branch into optional follow-up probes that the researcher uses when needed to clarify a response or explore an unexpected insight, giving flexibility while keeping the discussion anchored to the study's objectives. To enhance the credibility and validity of this instrument, the group-interview guide was subjected to expert validation, with questions reviewed by scholars and practitioners in writing pedagogy, ESL instruction, and educational research, who assessed their clarity, relevance, and alignment with the study's objectives and the theoretical framework. Feedback from these experts was used to refine wording and structure, ensuring that the guide effectively captures how engineering students incorporate AI into their writing from the very start of the planning process through to the final reflection on their work.

Data Collection - There was a systematic and carefully sequenced approach to data collection, carried out in the second semester of the academic year 2025–2026. The process began after the researcher obtained ethical clearance and formal approval from the College of Engineering. The study first moved to the quantitative phase, where 100 engineering students enrolled in the Civil (CE), Mechanical (ME), Electrical (EE), and Electronics Engineering (ECE) programs participated following the sampling strategy already described in the Source of Data section. Before administering the survey, the researcher conducted an orientation session that explained the objectives of the study, the procedures, and the expectations from participants. During this session, students read and signed an informed consent form stating that participation was voluntary, that their responses would remain confidential, and that their survey performance would not affect their academic standing. The AI Literacy and Writing Self-Regulation Scale was then administered online through a secure survey platform, allowing students to complete the questionnaire privately and at their own pace. The researcher began preliminary analysis as data was entered, identifying initial patterns and emerging themes related to AI use and self-regulated writing.

After the quantitative phase, the study proceeded to the qualitative phase. The researcher purposefully selected 10 participants from the 100 respondents based on their AI literacy scores and AI integration profiles, ensuring that these interviewees represented different degrees and forms of AI integration in their writing. These 10 students then took part in a group interview, conducted in a confidential, neutral, and quiet setting on the university campus to promote openness and honest interaction. The researcher once again reviewed the purpose of the study, clarified the voluntary nature of participation, and reiterated the right of participants to withdraw at any time. Written consent was obtained to audio-record the discussion. The group-interview sessions lasted approximately 30 to 45 minutes each. The researcher guided the discussion using the semi-structured group-interview guide, moving systematically from rapport-building to questions about AI integration across the planning, drafting, and reflection phases of writing, academic survival strategies, and ethical considerations. The full conversation was audio-recorded with participants' consent, then transcribed verbatim. Identifying information was removed or altered to maintain anonymity. To strengthen the ethical integrity and the credibility of the data, the researcher employed member checking: selected participants were invited to review and confirm the accuracy of the transcripts, ensuring that their statements were represented faithfully.

The systematic progression from the general, survey-based quantitative data to the more conversational, group-interview-based qualitative data allowed the researcher to triangulate evidence across different modes of data collection: individual responses and group interaction. This multi-phase, clearly sequenced data-collection process was aligned with the study's aims and provided a strong empirical foundation for describing AI-mediated writing practices and for refining the Awareness Human-centered Cognitive scaffolding Disclosure (AHCD)

Framework.

Data Analysis - A sequential explanatory approach was used in the study, where the quantitative results were analyzed first and then followed by a deeper qualitative examination. Descriptive statistics were applied to the responses of 100 engineering students to address the study's objective on AI literacy and self-regulated writing. The weighted mean was used to describe students' AI literacy across the three subscales of the AI Literacy and Writing Self-Regulation Scale: forethought, performance, and reflection. The scale was interpreted using these ranges: 4.50 – 5.00 Very High, 3.50 – 4.49 High, 2.50 – 3.49 Moderate, 1.50 – 2.49 Low, and 1.00 – 1.49 Very Low. This made it possible to describe whether students' AI literacy and self-regulation were very low, low, moderate, high, or very high, and to show how they generally engage with AI across the writing process.

To address the second objective on how students experience and view AI in their writing, the researcher analyzed qualitative data gathered from a group interview with 10 purposefully selected participants. The data were examined through thematic analysis following Braun and Clarke's (2006) steps: transcription, initial coding, grouping of codes into possible themes, refining and naming the themes, and defining the final themes in relation to the study's aims. Through this process, themes such as Academic Survival and Strategic Humanization emerged, showing how students try to manage academic pressure while using AI in ways that remain self-regulated and ethical. The analysis gave voice to the participants' own experiences and meanings, adding depth to the numerical results.

3. Results

This section detailed the results of the study, highlighting how engineering students used artificial intelligence for academic writing. The participants used AI for language improvement while they faced difficulties between their actual tool use and their knowledge of how the systems processed and arranged language.

3.1 AI literacy level of engineering students

This section presented the results of the survey on students' understanding, application, and ethical use of artificial intelligence (AI) in academic writing. Descriptive statistics, specifically weighted means and corresponding interpretations, were used to summarize the respondents' perceptions across the three dimensions. The findings were organized according to the indicators, weighted mean and interpretation presented in Tables 1, 2, and 3.

Table 1
Understanding of AI

Indicators	Weighted Mean	Interpretation
I understand what artificial intelligence (AI) means in the context of education.	4.42	High level
I can explain how AI systems generate or process language.	3.53	High level
I can differentiate between AI-generated text and human written text.	3.88	High level
I am aware of the strengths and limitations of AI tools in writing tasks.	4.38	High level
I understand how AI tools can support, but not replace, human creativity.	4.66	Very High level
Overall Weighted Mean	4.17	High level

The findings revealed a moderate overall understanding of AI, with a total mean of 4.17. The students felt most confident in what they made between the tool's role and their own, believing that AI should support rather than replace human creativity (WM = 4.66). This indicated that while students saw AI as a partner, they still placed a high value on their own creative work. However, the data revealed a lack of technical understanding regarding how these systems work. The lowest-rated indicator was the ability to explain how AI processes language (WM = 3.53). This gap indicated that while engineering students were comfortable using the tools, they often viewed them as a closed technique, focusing more on the final output than the actual linguistic process behind it

Table 2
Application of AI

Indicators	Weighted Mean	Interpretation
I use AI tools to brainstorm or generate ideas before writing.	3.93	High level
I use AI tools(e.g.ChatGPT,Grammarly) to check grammar and coherence.	4.12	High level
I use AI suggestions to improve the structure or vocabulary of my essays.	4.00	High level
I use AI tools to summarize or paraphrase text for better understanding.	4.08	Moderate level
I find AI tools helpful for revising my written work.	3.97	High level
Overall Weighted Mean	4.02	High level

The total application of AI technology received a moderate rating which resulted in 4.02. Students relied on AI as their primary language support because they used it to check their grammatical accuracy and writing coherence (WM = 4.12). The data showed that students used AI as a digital tool which helped them transform their engineering technicalities into proper academic English. Students showed less tendency to use the tool for main creative work during their first creative development phase. In contrast, the lowest rating went to using AI for brainstorming or generating ideas (WM = 3.93). Students showed dedication to original thinking because they wanted to keep control over their main ideas while using AI to help them create their final output.

Table 3
Ethics in AI Use

Indicators	Weighted Mean	Interpretation
I acknowledge AI-generated ideas or text in my written outputs.	3.62	High level
I avoid copying AI-generated text without modification or citation.	4.17	High level
I reflect on whether using AI aligns with my school's academic integrity policy.	3.94	High level
I consider the ethical implications of using AI tools for academic writing.	4.14	High level
I use AI responsibility to support, not replace, my learning process.	4.48	High level
Overall Weighted Mean	4.07	High level

The ethics portion reached an overall moderate mean of 4.07. The students expressed a strong commitment to using AI as a learning aid rather than a shortcut which was the highest-rated indicator. The students considered their tool usage to be ethical because it helped them understand the material better. The data showed that participants failed to disclose their actual tool usage despite their good intentions. The lowest-rated indicator was the formal acknowledgment of AI-generated ideas in their final outputs WM 3.62. The students wanted to learn but they used strategic methods to deny their AI usage. This gap showed that a mismatch between rules and reality may be occurring, where students feel forced to hide their collaboration with technology to ensure their academic survival.

AI Integration Strategies in three phases in writing - The section shows the results which researchers achieved from studying group interview and interview transcripts to examine how participants used Artificial Intelligence (AI) technology. The researcher organized their data into thematic categories to study writing process strategies which they needed to investigate for their research objectives. The section shows the results which researchers obtained from studying group interview to examine how participants used Artificial Intelligence (AI) technology. The researcher organized their data into thematic categories to study writing process strategies which they needed to investigate for their research objectives.

Pre-Writing AI Integration Strategies. Table 4 presents the thematic analysis results from group interviews and transcripts, showing how engineering students apply Academic Survival and Cognitive Scaffolding strategies during the pre-writing phase, with specific codes and participant excerpts illustrating AI use for time management and outline generation. The findings captured the two primary ways students turned to AI during pre-writing: as a lifeline for beating deadlines and as a tool for shaping raw technical ideas into workable outlines.

Table 4
Pre-Writing AI Integration Strategies

Theme	Description	Interview Excerpt
Academic Survival	AI as time-saving tool for initial planning under deadlines.	*"Lalo na pag gipit na talaga sa oras... yung AI po kasi napapadali talaga yung buhay." P1 (Especially when one is really constrained by time... because AI truly simplifies life")*
Cognitive Scaffolding	AI generates initial outlines to simplify technical concepts.	*"Ginagamit ko yung AI usually pag kunwari kailangan ko ng outline... kung ano ba yung dapat na laman ng introduction." P3 (I usually use AI when I need an outline... to determine what should be included in the introduction.)*

Drafting Phase (Content Development). Table 5 presents the thematic analysis from group interviews and transcripts, illustrating Cognitive Scaffolding (Expansion) strategies during drafting, where students use AI to develop structural frameworks and simplify complex concepts from their initial outlines, supported by participant excerpts.

Table 5
Drafting Phase (Content Development)

Theme	Description	Interview Excerpt
Cognitive Scaffolding (Expansion)	Students utilize AI to organize structural frameworks and simplify complex concepts from initial outline .	*"Ginagamit ko yung AI usually pag kunwari kailangan ko ng outline... kung ano ba yung dapat na laman ng introduction." P5 (I use the AI usually when, for example, I need an outline... on what should be the content of the introduction.)* *"Ginagamit ko rin yung AI pag ina-expand ko na yung outline ko para mas maging buo yung ideas ko sa draft." P9 (I also use the AI when I am expanding my outline to make my ideas more whole in the draft.)*

It presented how cognitive scaffolding carried over into drafting, with students relying on AI to expand those early outlines into full structural frameworks for their technical content.

Post-Writing AI Integration Strategies. Table 6 presents the thematic analysis, showing students apply advanced prompts with manual edits to evade detectors or reject AI entirely to preserve linguistic confidence, illustrated by participant excerpts.

Table 6

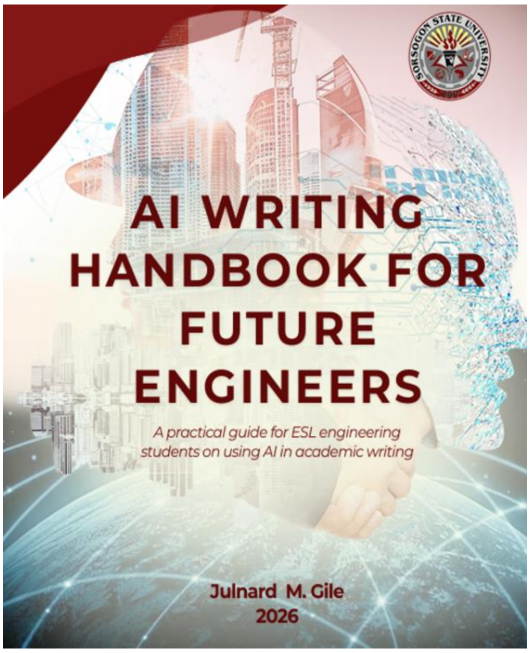
Post-Writing AI Integration Strategies

Theme	Description	Interview Excerpt
Strategic Humanization	Advance prompts plus manual edits to evade detectors.	*"Nagpopost sila ng mga prompts na hindi na nadedetect ng AI checking tools." P4 (They post prompts that are not detected anymore by AI checking tools.)*
Ethical Paradox	Complete AI rejection to maintain linguistic confidence.	*"I don't use AI because I'm confident in my skills in English.." P7*

During this period of review, the AIgenerated content was strategically humanize.It presented the dual reality of post-writing: most students refined AI outputs to escape detection tools, while one resisted AI entirely to protect their sense of authentic voice.

Proposed AI Writing Handbook for Future Engineers - The AI Writing Handbook for Future Engineers, together with the Awareness Human-centered Cognitive scaffolding Disclosure (AHCD) form, constitutes the main practical output of the study. The handbook is designed not merely as a set of instructions on AI tools, but as a pedagogical and ethical guide that aligns the use of AI with self-regulated learning, AI literacy, and the human-centered values highlighted in the study.

Figure 3



The quantitative findings show that students generally report moderate to high AI literacy and self-regulation scores, but they also reveal a clear sense of algorithmic opacity: students are comfortable using AI tools but less confident about how AI systems generate and process language. The lowest mean score (3.53) corresponds to the item asking students to explain how AI produces language, indicating a gap in their conceptual understanding of the technology that supports their writing. To address this gap, the handbook includes a generative logic module that explains, in plain and task-relevant terms, the basics of large language models and how they support ESL writing in engineering contexts. This module translates technical ideas into accessible language, helping students see AI as a transparent, semi-predictable partner rather than a mysterious black-box. By strengthening students' AI literacy at the conceptual level, the handbook supports the AHCD principle of Awareness, ensuring that students can make informed decisions about when and how to use AI instead of relying on invisible, unexamined processes.

The survey also reveals that students place a high value on the integrity of their own ideas. The relatively low mean score of 3.93, still generally high but the lowest among the subscales for using AI to brainstorm or generate ideas before writing suggests that many students care deeply about maintaining human-driven thinking at the outset of the writing process. The handbook responds to this by promoting AI use primarily for refinement and scaffolding for revising, restructuring, clarifying, and polishing rather than for generating core concepts. The AHCD form reinforces this value through an originality declaration section that requires students to state that the core engineering ideas and technical arguments are their own work. This section visibly separates human-generated conceptual thinking from AI-assisted linguistic processing, preserving student ownership over engineering concepts while still allowing AI to serve as a creative and supportive tool.

The qualitative findings further show that students engage in what can be described as strategic humanization to cope with heavy workloads and tight deadlines. They use AI to generate text, then reword, reorder, and reshape it until it resembles their own writing, in effect presenting themselves as critical editors rather than passive AI users. The study frames this pattern not as outright misconduct but as an emerging, often unacknowledged writing strategy shaped by the ethical paradox of wanting to succeed academically while not fully understanding how to use AI transparently. The AI Writing Handbook and the AHCD form together convert this informal survival strategy into an explicit, ethical practice. The handbook presents process of AI-writing cycles across the three writing phases, encouraging students to plan first in their own words, draft with manageable AI help, and then revise and humanize systematically. The AHCD form includes a Humanization Log that prompts students to document how they modified AI-generated text such as paraphrasing, restructuring sentences, adjusting vocabulary, and integrating citations thereby making their editing process visible and accountable.

In practical terms, the AI Writing Handbook and the AHCD form together serve as structured resources that help engineering students meet academic demands without sacrificing academic honesty. The handbook provides genre-specific writing tasks, AI-guided revision prompts, and metacognitive checklists aligned with the forethought–performance–reflection structure, while the AHCD form operationalizes the Awareness, Human-centeredness, Cognitive scaffolding, and Disclosure dimensions into concrete procedural steps. The output encourages students to view AI use not as a hidden shortcut but as a deliberate, documented, and reflective process: one that still requires them to engage cognitively, to own their ideas, and to show the complete trajectory of their technological interaction. By doing so, the handbook supports the study's goal of transforming AI-mediated ESL writing into a transparent, self-regulated, and ethically grounded practice that protects students' academic identity while enabling them to manage the linguistic and workload demands of engineering education.

4. Discussion

This section synthesizes the key findings and theoretical frameworks to demonstrate how the evidence supports the proposed AHCD-based approach for AI-mediated ESL writing among engineering students. By interpreting results through the lenses of Self-Regulated Learning, AI literacy, and the Zone of Proximal Development, the discussion justifies the practical implementation of the AI Writing Handbook and the AHCD form.

***Current AI Skills in Engineering* -** This section reviews the results on the AI literacy of engineering students in their understanding of AI, application of AI, and ethics in us. Despite the recognition of the importance of AI as a support tool to human creativity among the students, the technical weaknesses can be observed in the fact that they are unable to expound on language processing and accept AI-generated ideas; therefore, improvements can be made to make them stronger in the professional development.

Implications of AI Understanding. The moderate level of AI literacy indicates that most students are comfortable using AI tools, but their understanding of AI remains more functional than technical. They know that AI can help them write faster, improve clarity, and reduce grammatical errors, yet they are less certain about how it processes language, selects information, or generates text. This pattern is important because higher education research shows that students often become confident prompt users before they develop a deeper understanding of AI's mechanisms and limitations, which can lead to over-trust in polished outputs (Eager & Brunton, 2023; Zhai et al., 2024). In this study, that pattern appears in the tendency of students to use AI for finishing tasks on time without always reflecting on how the text is produced. The implication is that AI literacy instruction should move beyond simple tool use and include lessons on how generative AI works, where its limitations lie, and why critical reading of AI output matters.

At the same time, the students show a clear awareness of the boundary between human and machine work. They describe AI as an assistant or partner rather than the primary writer, which reflects a human-centered view of AI use. They see themselves as the creators of ideas and arguments, while AI mainly helps with grammar, organization, and sentence-level refinement. This is a positive finding because it shows that students do not fully surrender authorship to AI; instead, they preserve their role as the main decision-makers in the writing process. Similar studies in engineering and higher education report that when students are guided to evaluate AI critically, they are more likely to treat AI as a support tool rather than a replacement for intellectual work (Kasneci et al., 2023; Zhai et al., 2024). The implication is that instructors should strengthen this human-centered attitude by teaching students how to evaluate, edit, and justify AI-assisted writing decisions.

The Technology Acceptance Model helps explain why students use AI so readily. Their responses suggest that they perceive AI as useful and easy to use, and these two beliefs make them more willing to integrate it into their writing workflow (Davis, 1989). They report that AI lowers cognitive load, improves text quality, and becomes part of their routine once they learn how to prompt it effectively. This is consistent with prior studies showing that perceived usefulness and ease of use strongly predict AI adoption in higher education (Alshahrani, 2024; Zhai et al., 2024). However, the present findings also show that high acceptance does not necessarily mean deep understanding. Students may rely on AI confidently while still lacking the conceptual knowledge needed to explain how models are trained, how outputs are generated, or how bias appears. The implication is that usefulness alone is not enough; students also need structured AI literacy education that develops critical judgment alongside technical confidence.

The low score on the item asking students to distinguish AI-written from human-written text points to a more serious gap in AI literacy. Students may appreciate fluent AI-generated text and treat it as credible because it looks polished, even when the content may be incomplete, biased, or weak in reasoning. This is a concern because research on AI-assisted writing shows that learners often over-trust AI output when it appears professional and grammatically correct, even if they have not checked its argument structure or evidence base (Kasneci et al., 2023; Rudolph et al., 2023). The implication is that writing classes must include explicit training in critical reading of AI-generated output. Students need to learn not only how to use AI, but also how to question it, compare it with their own thinking, and recognize when it produces surface-level improvement without strong substance.

From a self-regulated learning perspective, these findings are also significant. SRL theory emphasizes that effective learners plan, monitor, and evaluate their work across the forethought, performance, and reflection phases (Zimmerman, 2000). In the present study, students already use AI in ways that support performance, especially during drafting, editing, and polishing, but their weaker conceptual understanding suggests that their forethought and reflection phases still need support. Research on SRL and AI similarly shows that AI can strengthen learning when it supports goal setting, monitoring, and reflection, but it can also weaken SRL when students rely on it too passively (Li & Kim, 2025; Park et al., 2024). The implication is that AI use should be embedded within structured writing routines that require students to set goals, explain their choices, and reflect on how AI affects their writing process.

The practical implication is clear: engineering and ESL writing instructors need to pair AI tasks with critical evaluation activities. The AI Writing Handbook for Future Engineers can help by explaining in accessible terms how large language models work and by guiding students through planning, drafting, and reflection tasks that require them to compare, annotate, and critique AI output. This aligns with recent instructional work showing that students benefit when they are taught to generate prompts, inspect responses, and evaluate AI output using clear criteria (Kasneci et al., 2023; Zhai et al., 2024). In the AHCD framework, this also supports Awareness, Human-centeredness, Cognitive scaffolding, and Disclosure. In practice, this means AI-supported writing becomes a metacognitive and ethical routine rather than a mere shortcut.

AI Use in the Writing Process. The findings on AI application show that engineering students mainly use AI for surface-level refinement, especially grammar checking, coherence improvement, and structural polishing. The moderate weighted mean suggests that students integrate AI at specific points in the writing process, especially during drafting and revising, but they do not treat it as a full substitute for their own work. This is a useful pattern because it shows that students already use AI strategically, reserving it for later-stage polishing rather than for generating the full content of their papers. Similar studies report that students prefer AI for revising and improving clarity rather than for producing original arguments from scratch, especially when they want to preserve ownership of their ideas and technical content (Eager & Brunton, 2023; Kasneci et al., 2023). The implication is that instructors can build on this existing behavior by teaching students how to use AI more intentionally and reflectively.

This pattern also fits well with self-regulated learning. Students appear to use AI mostly during the performance and reflection phases, while keeping the planning phase largely under their own control. That means they already show some phase-based regulation of AI use, which is consistent with SRL theory (Zimmerman, 2000). However, the moderate AI literacy level suggests that their regulation is still fragile. Some students may not yet reflect deeply enough on how AI affects tone, argument quality, or authorship. The implication is that they need more explicit scaffolding so they can move from simply using AI to using it in a way that strengthens their writing decisions and metacognitive awareness.

For teaching, this means AI-integrated writing tasks should not only focus on output quality but also on process quality. The AI Writing Handbook for Future Engineers can support this by guiding students through a writing cycle where they first generate ideas independently, then draft with limited AI help, and finally use AI for polishing while documenting what changes they accept or reject. This kind of structure helps students retain control over meaning while using AI as a language-support tool. It also matches studies showing that students learn better when AI is used as a scaffold within a clearly defined writing process rather than as an invisible helper (Li & Kim, 2025; Park et al., 2024). The implication is that refinement-oriented AI use becomes more educational when it is paired with reflection and disclosure.

At the policy level, these findings support the need for nuanced AI guidelines in engineering education. Students in this study already treat AI as a polishing tool, which means institutional policies should not simply ban AI or treat all use as misconduct. Instead, policies should clarify what kinds of support are acceptable, when disclosure is needed, and how students can show ownership of their work. This approach is consistent with recent calls for AI policies that are descriptive, supportive, and aligned with actual student practices rather than purely punitive (Kasneci et al., 2023; Zhai et al., 2024). The practical implication is that departments can use the AHCD framework to create assignment instructions, rubrics, and AI-use statements that reflect how students really use AI in writing.

Ethical Regulation and Disclosure. The findings on ethics show a gap between students' ethical intentions and their actual disclosure practices. Students generally believe that AI is acceptable when it supports learning, but they struggle with formal citation, acknowledgment, and transparency. This matters because ethical AI use is not only about avoiding plagiarism; it also involves being honest about how AI contributes to the writing process and whether the student remains the primary author of the work (Cotton et al., 2023; Perkins & Roe, 2023). In the present study, students seem to view AI as a responsible support tool, but they do not always see the need to document its role clearly. The implication is that good intentions are not enough; students also need concrete models of how to disclose AI use in a transparent and academically acceptable way.

The low scores on items about recognition of AI-generated ideas suggest that students do not yet have a stable norm for disclosure. They may believe that if they edit AI output, it becomes fully theirs, which leads them to treat AI assistance as something private rather than something that should be acknowledged. Similar studies report that students often feel uncertain about how to represent AI-assisted writing when institutional policies are vague or incomplete (Ajjawi et al., 2024; Perkins & Roe, 2023). The implication is that universities need to move beyond general warnings and give students clear disclosure procedures, sample statements, and examples of acceptable AI use. This makes AI ethics more practical and less ambiguous.

From an SRL perspective, the ethical gap also affects self-monitoring. If students do not reflect on or record how AI contributes to their writing, they weaken the metacognitive side of self-regulation. SRL requires learners to monitor not only the quality of their work but also the process through which that work is produced (Zimmerman, 2000). The present study suggests that students are still developing this habit when AI is involved. The implication is that ethical reflection should be built into writing tasks, not treated as an afterthought. Students need prompts that ask them to identify what AI did, what they changed, and what they decided to keep or remove.

The AI Disclosure Template and AHCD framework address this needs directly. They make disclosure visible, systematic, and teachable by asking students to name the tool, describe its purpose, and explain how they revised the output. This is important because it transforms disclosure from a hidden moral burden into a routine part of academic writing. Recent literature supports this approach, emphasizing that AI-integrity policies work best when they are supportive and instructional rather than purely punitive (Ajjawi et al., 2024; Cotton et al., 2023). The implication is that engineering programs should teach AI ethics through practice, not just rules.

The findings show that engineering students already use AI in ways that are practical, selective, and often supportive of their writing process, but their understanding of AI, their strategic use of it, and their disclosure habits still need strengthening. The main implication is that AI literacy should be taught together with SRL and ethics, not as separate concerns. Students need to know how AI works, how to use it effectively, and how to disclose it responsibly. The AHCD framework and the AI Writing Handbook for Future Engineers provide a coherent response to this need because they connect awareness, human-centeredness, cognitive scaffolding, and disclosure in a way that is usable in actual classroom practice.

Future Engineering Strategies on AI Integration - This section discusses how engineering students integrate AI across the three writing phases: pre-writing, drafting, and post-writing. It shows that they use AI for cognitive scaffolding, linguistic refinement, and self-editing, while also negotiating the ethical tension between using AI for academic support and maintaining originality as writers.

Academic Survival. The data shows that engineering students frequently turn to AI during the pre-writing phase under intense pressure, treating it as a logistical necessity for academic survival rather than a creative or pedagogical choice. As P3 put it in the group interview, *"Gipit na kami sa oras, kaya AI na lang agad mag-outline para mapabilis"*. (We were pressed for time, so we just used AI immediately to outline so it would be faster). This type of response appears repeatedly across the transcripts as students describe AI as their first response when multiple deadlines for reports, coding projects, and technical assignments collide within short periods. They do not frame AI as a luxury or optional enhancement; instead, they see it as a practical, almost compulsory coping mechanism that helps them manage workload and still meet submission requirements. Every group-interview participant acknowledges using AI in these "crunch" moments, often for quick outlines, topic clustering, or structure generation, which they then treat as a scaffold for their own drafting. This pattern is consistent with recent findings that students adopt generative AI most readily when it helps them cope with exhaustion and crowded schedules by reducing the apparent difficulty and time cost of writing tasks (Sullivan et al., 2023; Zhai et al., 2024).

This pattern reveals that writing is often secondary to engineering problem solving in students' priorities: AI is used mainly to close the efficiency gap, allowing students to allocate more mental energy to technical reasoning and problem solving. The AI generated outline or draft becomes a way to make it fast while preserving space for calculations, coding, and experimentation. As P8 explained, "Mas importante yung solution, so AI lang muna yung writing, para hindi ako mahuli sa lab report." (The solution is more important, so AI first for the writing, so that I won't be late with the lab report). This mindset positions ESL writing as a logistical burden rather than a central learning goal, and AI functions as a tool that compresses the time needed for language related planning (Kasneci et al., 2023; Rudolph et al., 2023).

From a self-regulated learning (SRL) perspective, this pattern reflects a load-driven form of regulation: students use AI to manage their time and cognitive load, but they do not always engage deeply with the planning and organizational work that SRL models assign to the forethought phase (Zimmerman, 2000). Instead of internalizing outlining and structuring as skills, they delegate these tasks to AI, which can create a kind of dependency that weakens their independent pre-writing abilities. Over time, this may affect their capacity to produce well-organized engineering documents in professional settings, where structured, comprehensive reporting is crucial. Recent SRL-and-AI studies similarly warn that when AI is used mainly as a shortcut under pressure, it supports short-term task completion but can undermine long-term development of planning and strategic writing skills (Li & Kim, 2025; Park et al., 2024). The results therefore suggest that AI-mediated pre-writing, as it currently stands, is more about workload management than about deep SRL, especially in the forethought phase.

The study's findings also align with the Technology Acceptance Model (TAM), which emphasizes that users adopt technology when they perceive it as useful and easy to use, particularly under pressure (Davis, 1989). Sullivan et al. (2023) show that generative AI becomes a primary coping mechanism among students facing exhaustion and crowded schedules because it saves time and reduces the perceived difficulty of writing tasks. In the present study, the "gipit sa oras" (Time-constrained) pattern and the consistent use of AI for quick outlines under workload stress confirm that perceived usefulness under time pressure strongly predicts AI adoption. Unlike studies that investigate AI use in elective or low-stakes writing contexts, however, these results extend TAM to compulsory ESL writing in engineering, where AI is not a luxury but a survival strategy embedded in high-stakes, technically dominant curricula. This extension supports emerging arguments that workload is a root catalyst for AI adoption, not merely a background condition (Kasneci et al., 2023; Zhai et al., 2024).

The practical implications for teaching and program design are therefore clear. Academic programs in engineering can redesign schedules to reduce the clustering of high-load assessments and introduce hybrid workshops that combine AI-generated outlines with guided manual revision. For example, students might first generate an AI-assisted outline, then reconstruct or modify it by hand, explicitly comparing AI-suggested structures with their own reasoning and priorities. Similar "AI-plus-revision" approaches are shown to support more reflective and critical use of generative tools (Eager & Brunton, 2023; Li & Kim, 2025). ESL instructors can also teach students to log their AI usage patterns, noting when they turn to AI, what they ask it to do, and how they integrate its output; this kind of tracking turns academic-survival tactics into visible, analyzable habits rather than hidden coping moves. Educational technology designs, in turn, can move beyond simple outline generation and include prompts that ask students to justify their reliance on AI or to revise an AI-generated structure before accepting it.

At the policy level, the study supports reforms that acknowledge AI as a common, workload-driven coping mechanism rather than an isolated ethical problem. If institutions continue to treat AI-assisted writing primarily as an integrity issue, they risk misreading the underlying causes: students use AI because their schedules and expectations do not leave room for extensive, self-regulated writing planning. Recent discussions in higher education caution that punitive, AI-focused misconduct policies often fail when they ignore structural workload pressures and students' lived experiences (Ajjawi et al., 2024; Perkins & Roe, 2023). Policies that combine workload restructuring with AI-transparency requirements—such as mandatory usage logs or AI-use statements in lab reports—can better align institutional expectations with students' real-life pressures. The present findings, especially the repeated verbatim descriptions of being "gipit sa oras"(Time-constrained) and the consistent use of AI in crunch moments, indicate that workload-sensitive ESL pedagogy and assessment redesign are urgently needed.

In conclusion, the academic-survival data highlight a time-driven, pre-writing AI-use pattern among engineering students, one that is deeply embedded in their experiences of heavy schedules and technical demands. The verbatim responses show that students see AI as a logistical tool for academic survival, not as a creative or purely pedagogical enhancement. By situating these findings within TAM and broader AI-in-education research, the study contributes to a more nuanced understanding of how stress and workload shape AI-assisted writing and how curricula can be restructured to support more sustainable, reflective, and ethically grounded writing practices.

Cognitive Scaffolding. It highlights how engineering students use AI not to replace their technical thinking but to help them structure and articulate their work in English. The data reveal that students engage AI during the pre writing and drafting phases, first to generate outlines (Table 4) and later to expand these into more complete structural frameworks (Table 5). In the group interview transcripts, participants describe feeding AI with their own technical content system designs, calculations, protocols, and engineering explanations and then asking AI to arrange, rephrase, or make it flow better instead of to generate content from scratch. P6 explains, "I type my bullet points about the design, then I ask AI to make it into paragraphs that connect better," while another notes, "The ideas come from our computations; AI just helps put them in order so it sounds like proper engineering English." No participant reports AI originating core technical concepts; instead, they consistently describe AI as restructuring, sequencing, and refining the presentation of knowledge they already possess. This pattern echoes recent work showing that generative AI is most pedagogically useful when it supports organization, coherence, and language expression while students retain responsibility for disciplinary ideas and reasoning (Kasneci et al., 2023; Zhai et al., 2024).

This pattern positions AI as a genuine cognitive scaffold for ESL engineering students, bridging their technical expertise with academic English structures that traditional instruction often does not fully cover. Generative AI effectively becomes an organizing mind that helps them transform scattered bullet points and fragmented notes into coherent paragraphs and sections. For example, a student working on finite-element analysis inputs process calculations and asks AI to write a short explanation that connects the steps, resulting in a more readable description without altering the underlying engineering reasoning. In this way, AI supports the translation of complex engineering ideas into accessible prose, enhancing assignment sophistication while preserving intellectual ownership of core content. Conceptual and empirical work on AI-based scaffolding similarly argues that generative AI can scaffold planning, organization, and reflection—particularly when students supply the ideas and AI handles linguistic and structural work (Chiu & Fujita, 2025; Kim & Xu, 2025).

This use of AI also aligns closely with Vygotsky's Zone of Proximal Development (ZPD), which describes the distance between what learners can do independently and what they can achieve with the help of a more knowledgeable other (Vygotsky, 1978). In this context, AI functions as a more knowledgeable other for language and organization: it enables students to produce texts that are more sophisticated and coherent than those they might achieve alone in English, while they remain responsible for generating the technical content and evidence. A recent classroom study on AI-based scaffolding shows that when AI is integrated into phased, scaffolded writing tasks, students' learning of complex practices improves and their independent performance strengthens once support is gradually withdrawn (Lee & Huang, 2025). Parallel work on generative-AI "agents" reports that AI-assisted prompts and structured feedback can enhance students' comprehension and compositional quality when the human writer continues to provide the core ideas (Oh et al., 2024). The present findings fit this pattern: participants describe using AI to decide which content to include, which ideas to link together, and how to sequence arguments, but the actual technical explanations and computations remain their own.

From a self regulated learning (SRL) and AI literacy perspective, this cognitive scaffolding pattern has both strengths and risks. On the positive side, the data show that students already demonstrate emerging SRL by deliberately using AI at points where they recognize a gap in this case, structuring and articulating technical content in English. P2 and P10 plan their use of AI "I'll do the calculations first, then ask AI to help write the explanation", monitor how AI reorganizes their ideas "I check if the order still matches my process", and revise the AI generated text to better reflect their intentions. This reflects SRL in the performance and reflection phases: students deploy AI as a targeted strategy to manage the cognitive load of language and organization while keeping control over the (Zimmerman, 2000). However, recent research on AI driven scaffolding warns that prolonged reliance on AI for structuring may weaken independent forethought and planning skills if not paired with explicit instruction (Huang & Luo, 2025; Park et al., 2024). The present cognitive-scaffolding data echo this caution: engineering students benefit from AI support in structuring, but they also need guided practice in outlining, sequencing, and designing report sections on their own so that their long-term writing agency is not compromised.

The practical implications for ESL and engineering writing instruction are therefore clear. The study suggests that instructors design tasks where students co-construct structure with AI instead of passively accepting AI organization. For example, students might submit three artefacts: their raw bullet-point notes, an AI-structured version, and a brief reflection explaining which changes they keep, modify, or reject. Similar "compare and justify" activities are shown to strengthen students' metacognitive awareness of how AI shapes their texts (Chiu & Fujita, 2025; Kim & Xu, 2025). The AI Writing Handbook for Future Engineers can incorporate scaffolding contracts or checklists that require students to document what they provide and what AI handles, making the AI–human partnership transparent. Rubrics can be adjusted to emphasize conceptual rigour, clarity of reasoning, and logical sequencing rather than only linguistic polish, so students understand that AI-assisted fluency is not sufficient; the strength of their engineering thinking must remain central.

At the policy level, institutions can explicitly recognize AI as a legitimate cognitive scaffold within students' ZPD while still requiring documentation of its role in structuring and language. This approach aligns academic integrity with real-world practice by acknowledging that AI-supported organization is now part of authentic engineering communication, if students are transparent about how they use it (Ajjawi et al., 2024; Perkins & Roe, 2023). For future research, longitudinal and experimental studies can examine how different patterns of AI-supported structuring affect students' independent outlining and planning skills over time and whether ZPD-based, guided scaffolding tasks can strengthen, rather than erode, their long-term self-regulated writing abilities

Strategic Humanization. It centers on the post writing phase, where engineering students actively reshape AI generated text to make it sound authentic and "human," often to avoid detection. The data show that this phase is dominated by dual integrity dynamics: most participants use advanced prompting and careful manual editing to evade detection tools, while one participant explicitly rejects AI to preserve the integrity of their own unassisted writing. In the transcripts, participants describe their tactics in direct, verbatim language. P3 explains, "I let AI write the first draft, then I change the sentence order and the transition words, so it doesn't look like AI anymore." Another adds, "I switch between ChatGPT and Grammarly, and sometimes I even use three different tools, so the similarity score goes down enough." These phrases appear across all group interview transcripts, showing that multi platform tool has become a standardized, community shared practice. At the same time, the one participant who refuses AI states, "If I use AI, it's not really mine. I prefer to write everything on my own, even if it takes longer," reflecting a strong commitment to authenticity and personal authorship.

These verbatim responses reveal how students reframe concealment tactics as a form of advanced refinement. Participants describe spending significant time manually rephrasing, restructuring, and re prompting AI generated text to align it with their own voice and reasoning. One student share, "I spend at least two hours just changing the transitions and adding my own examples, so in the end it feels like it came from me, not the AI." Other notes that their peers teach each other tricks, such as rotating AI platforms and rephrasing key phrases, to manipulate similarity scores without substantially changing the content. This behavior captures a cat and mouse dynamic between detection systems and AI savvy students, where effort is diverted from deep content mastery toward either concealment or independence. Similarly documents that students use AI both to generate text and to outmaneuver detection systems, arguing that existing anti-plagiarism tools often lag behind technically adept users (Perkins,2023). It also find high rates of tool-jumping and multi-platform use, confirming that students deliberately switch AI tools to manage similarity scores (Cotton et al. (2023).

From an SRL and Self-Determination Theory (SDT) perspective, these patterns reflect a tension between autonomy, competence, and relatedness (Deci & Ryan, 2000). Students who invest time in manually rephrasing, restructuring, and re-prompting AI are, on one level, demonstrating SRL: they plan how to use AI, monitor its output, and revise to match their own standards. However, because much of this energy is directed toward concealment rather than deeper content mastery, their regulation is misaligned with educational goals. It explain the resistance side of this pattern through SDT, showing that students who reject AI are motivated by a strong sense of autonomy and authenticity and want to demonstrate genuine competence (Bearman and Ajjawi, 2023). The outlier participant in the present study who refuses AI fits this profile, framing AI use as a threat to their authorship and integrity. It further argue that post-pandemic assessment policies, designed for traditional cheating, do not fully account for generative AI, creating an inevitable paradox where students feel forced to choose between using AI effectively and complying with rules that treat all AI assistance as suspicious (Perkins and Roe,2023).

Emerging work on ethical generative-AI use in engineering education echoes the need for transparent, skill-based approaches. Recent frameworks propose that instructors explicitly teach prompt engineering, ethical evaluation, and documentation of AI use in both coding and writing, so that AI becomes a visible part of the learning process rather than a hidden accomplice (Kasneci et al., 2023; Zhai et al., 2024). A multidimensional model of human–AI collaboration in writing similarly emphasizes that AI can assist with drafting, revising, and editing without replacing human agency when students remain in control of core ideas and reasoning (Li & Kim, 2025). Library-based ethical prompting guides recommend clear, constrained prompts and explicit disclosure, arguing that AI should enhance learning rather than perform work that students present as entirely their own (Ajjawi et al., 2024). The present study's findings align with these recommendations: students already engage in sophisticated humanization and concealment behaviours, and the challenge is to turn these into teachable, ethical skills rather than leaving them as hidden workarounds.

The practical implications for ESL and engineering writing instruction are therefore both clear and nuanced. The study suggests that many concealment tactics can be reframed as legitimate prompt-engineering and editing skills, taught openly in the classroom. Instructors can guide students to practise ethical humanization: using AI to generate initial drafts, then systematically re-writing, restructuring, and reflecting on how they modify AI-generated text. The AI Writing Handbook for Future Engineers can include explicit ethical-humanization guidelines, such as what students may legitimately ask AI to do, how to annotate AI-assisted revisions, and how to write brief disclosure statements that explain their use of AI. This approach shifts assessment from a detection-driven model to a transparency-driven model, in which students are rewarded for reflecting on and documenting their collaboration with AI rather than for evading detection systems (Cotton et al., 2023; Perkins, 2023).

At the policy level, the study supports a move away from prohibition-oriented AI policies toward disclosure-based frameworks that acknowledge diverse student approaches. Engineering and technical institutions can develop AI-use statements that distinguish between using AI to generate full content without attribution and using AI as a scaffold for revision and refinement with clear documentation. The present findings show that both concealment tactics and outright resistance are real-world responses to confusing or punitive policies and that more reasonable policies can recognise AI-assisted writing as a legitimate, context-specific practice when it is transparently reported (Bearman & Ajjawi, 2023; Perkins & Roe, 2023). For future research, the study opens avenues for exploring how different types of AI-disclosure systems affect students' integrity decisions, how prompt-engineering and humanization skills relate to deeper content mastery, and how strategic humanization can be transformed into a scaffolded, metacognitive practice rather than a hidden workaround.

Proposed AI Writing Handbook for Future Engineers - The output contains the complete *AI Writing Handbook for Future Engineers*, a practical 30+ page guide that directly implements the key findings from Objective 3 on strategic humanization in the post-writing phase. This handbook transforms the raw qualitative data on concealment tactics, multi-platform tool-jumping, and authenticity concerns into classroom-ready tools that address the dual integrity dynamics identified in Table 6. Rather than treating students' behaviors as problems to punish, the handbook operationalizes the AHCD Framework (Awareness, Human-Centered Design, Cognitive Scaffolding, Disclosure) as the core structure, turning hidden hacks into documented, ethical practices that resolve the moral tensions between efficiency and self-efficacy.

The transcripts revealed engineering students spending hours on advanced prompting, sentence reordering, and rotating AI platforms like ChatGPT and Grammarly to evade detection, while one outlier rejected AI entirely with the sentiment *"If I use AI, it's not really mine."* The handbook responds through Chapter 5's templates that capture these exact behaviors transparently: Template 2 AI-Use Log documents AI tool used, How AI helped, and What I changed/rewrote myself, making covert tool-jumping visible and accountable. Template 3 One-Sentence Disclosure provides standardized phrasing like *"AI tools were used for grammar checking and limited sentence-level rephrasing. All main ideas, structure, and technical explanations were written by the student,"* eliminating the ethical uncertainty that drove concealment.

Chapter 3.3 Revising Phase organizes the two hours rephrasing transitions pattern into Activity 3.3, where students read drafts aloud, highlight too smooth AI sections, and manually rewrite them directly addressing the generic voice problem noted by Perkins (2023). Chapter 4 implements the AHCD Framework as a response to theoretical synthesis, with each element matching verbatim student concerns: Awareness requires pre-writing decisions about AI boundaries; Human-centered Design uses Activity 4.1 to compare/merge student vs. AI drafts; Cognitive Scaffolding limits AI to transitions/sentence-level support; and Disclosure resolves ownership fears through routine documentation.

From a self-regulated learning (SRL) perspective, the data showed students demonstrating forethought the planning prompts, performance monitoring the checking outputs, and reflection the rephrasing for voice, but misdirecting these toward detection evasion. Chapter 2 reframes this through Zimmerman's phases: Forethought via Ch. 3.1's Outline Comparison; Performance via Ch. 3.2's Controlled Drafting, AI limited to suggest transitions; Reflection via Ch. 3.3's AI-Use Log asking, *"What did I rewrite myself?"* The handbook's engineering-specific examples civil engineering lab reports on beam-column interaction, mechanical heat engines, electrical design descriptions match participant contexts exactly, following their workflow of raw technical bullets form AI structuring to manual humanization upto disclosure.

Chapter 5's Weekly Routine the 3-day cycle: Plan to Draft up to Reflect creates the workload-sensitive assessment redesign called for in Objective 3, preventing panic-driven output by spacing AI use and generating evidence of learning for instructors. Template 1 the AI-Writing Checklist becomes the new assessment artifact, with checkboxes proving forethought, performance control, and reflection. This rejects detection-dependence entirely, recommending rubrics valuing conceptual rigor over linguistic polish.

The handbook perfectly closes the research-to-practice loop for Objective 3. Students who currently hide tool-jumping will document it transparently; the authenticity-seeker gets validation through structured disclosure. The citations find practical form in tools that transform cat-and-mouse concealment into ethical prompt-engineering education. This file demonstrates concrete research impact: from verbatim concealment tactics to institutionalized AHCD-guided writing across Sorsogon State University's engineering programs, fulfilling the study's call for assessment evolution beyond detection toward transparency frameworks.

5. Conclusion and recommendation

The study concludes that ESL engineering students integrate generative AI across distinct writing phases to address linguistic and workload barriers, despite demonstrating limited technical understanding of large language models through low AI processing assessment scores. To address the primary research objectives, three distinct behavioural patterns emerge: Academic Survival highlights a time-pressured, pre-writing reliance on AI-generated outlines; Cognitive Scaffolding demonstrates deliberate structuring of technical content during drafting while actively preserving engineering ownership; and Strategic Humanization captures post-writing concealment tactics alongside authentic resistance, resulting in a persistent disclosure deficit rooted in efficiency-integrity tensions. The overall implication of these findings indicates that conventional detection-and-punishment systems prove completely obsolete against technically adept students mastering multi-platform tool-jumping. Ultimately, these findings signify that the intersection of intense workload, technical identity, and language demands uniquely shapes AI practices within compulsory ESL engineering contexts, underscoring an urgent academic need for transparency frameworks over outright prohibition.

Based on these conclusions, it is recommended that universities discontinue adversarial AI-detection mechanisms and instead require students to document their AI usage through the AHCD Framework (Awareness, Human-Centered Design, Cognitive Scaffolding, Disclosure), operationalized via the *AI Writing Handbook for Future Engineers*. To achieve this, ESL programs have designed structured pathways that integrate AHCD Forms, AI-Use Logs, and hybrid workshops blending AI outlines with manual revision, alongside rubrics prioritizing conceptual rigor over linguistic polish. Furthermore, language educators possess the necessary Handbook templates to teach verification against engineering sources, critical editing, and routine documentation, effectively transforming hidden hacks into professional competencies. Engineering curricula similarly embed AHCD-guided tasks directly into standard lab reports and design documents to reinforce authentic ownership. Finally, future research has established clear trajectories toward longitudinal and experimental designs that systematically test long-term AHCD effects on student linguistic self-efficacy, independent structuring skills, and ethical decision-making across technical disciplines.

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