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From Tool to Mirror: How Engagement Patterns Moderate Outcomes in AI-Assisted Academic Writing

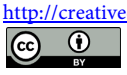
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Abstract

Generative AI tools are increasingly applied in academic writing, yet their impact on learners remains controversial. This study moves beyond the question of whether AI helps or hinders writing by examining how students engage with AI. Drawing on qualitative data (including process logs, AI dialogue transcripts, think-aloud recordings, interviews, and textual drafts) from nine Chinese university students who used DeepSeek to revise an argumentative essay, we employed grounded theory to identify four distinct engagement patterns: Strategic Performer, Pragmatic Optimizer, Architectural Leverager, and Critical Integrator. These patterns were associated with different writing outcomes moderated writing outcomes and psychological experiences. Strategic Performers showed inflated, externally derived self-efficacy; Pragmatic Optimizers displayed stable, tool-based efficacy; Architectural Leveragers experienced fragile, ambivalent efficacy; and Critical Integrators achieved authentic, learning-based efficacy. Ownership and anxiety also varied accordingly. We propose the metaphor of AI as a "cognitive mirror" to capture how its effects depend on the depth of learners' reflective engagement. The findings offer a diagnostic typology for researchers and educators by suggesting that cultivating critical integration is essential for transforming AI from a simple tool into a mirror for self-regulated learning.

Subject Areas

Artificial Intelligence, Linguistics

Keywords

Engagement Pattern, AI-Assisted Academic Writing, Moderate, Cognitive

Mirror, Self-Regulated Learning

1. Introduction

Academic writing, which entails proficiency in diverse areas such as coherence, grammar, and vocabulary, is crucial to language development [1]. With the advent of ChatGPT in 2022 and the continuous successive updates and optimization of AI models, the easy access to generative artificial intelligence (GenAI) tools for writing tasks has irrevocably altered the landscape of academic writing [2] [3]. Exemplified by ChatGPT5, those GenAI tools provides a novel avenue by offering instant assistance with drafting, editing, and idea generation [4]. As a consequence, this technological shift has ignited a heated debate within higher education regarding the impact of AI assistance to academic writing on learners.

Initial research into AI-assisted writing presents a paradox. On the one hand, studies show that AI can enhance motivation, self-efficacy, and writing quality by providing scaffolding and reducing cognitive load [5] [6]. On the other hand, evidence points to the risks of over-dependency, superficial learning, and attenuated critical thinking, particularly when engagement is passive or uncritical [7] [8]. With a body of contradictory evidence, the question "Does AI help or hinder the writer?" has become overly simplistic and requires re-examination.

Fortunately, a promising shift in perspective is emerging, focusing on how students interact with AI in writing. For instance, the role of self-regulated learning (SRL) strategies in shaping effective AI use is beginning to be recognized [9] [10]. Equally noteworthy is the recent work by Kim *et al.* which analyzed different student-AI interaction (SAI) patterns and links them to variations in academic writing performance, marking a crucial step beyond tool-centric analysis [3]. However, it primarily ascribes these patterns to students' level of AI literacy, a static prior proficiency factor, overlooking the interactive dynamics that are driven by and, in turn, reshape learners' moment-to-moment metacognitive strategies, motivational goals, and psychological states throughout the writing process. In fact, a recent study based on social cognitive theory has shown that, among the individual factors influencing EFL students' effective use of generative AI, self-regulation and critical thinking are the strongest predictors, surpassing the role of traditional writing skills and highlighting the central role of cognitive processes [11]. Nevertheless, a comprehensive, evidence-based typology of participatory patterns and a theoretical framework that clearly explains how these patterns influence psychological and textual outcomes remain lacking.

This study, focusing on the DeepSeek platform instead of the predominant ChatGPT [12], moves beyond asking whether AI is good or bad to explore individual engagement patterns with AI by examining human-AI collaboration in writing to explain how and why its effects vary so dramatically. It argues that the primary educational imperative is to cultivate the metacognitive awareness and

skills necessary for transforming AI from a simple tool into a mirror for self-regulated learning.

2. Literature Review

2.1. AI in Academic Writing

The integration of generative AI (GenAI) into academic writing has generated both enthusiasm and caution. Numerous studies document its potential to enhance motivation and engagement [5] [12], provide personalized feedback [13], and improve writing self-efficacy and performance [6] [14] [15]. The benefits are often attributed to AI's capacity to lower barriers, offer instant support, and create responsive learning environments [10].

Conversely, a parallel body of research highlights significant risks. The most prominent concern is technological dependency, which may undermine sustained cognitive effort and long-term skill development [7] [16]. Zhang *et al.* found that AI dependence correlated with lower academic self-efficacy and higher academic stress [17]. Zhang and Xu further noted that temporary self-efficacy gains may be offset by reduced intrinsic motivation and weakened autonomous capability [16]. Additionally, students may reject AI feedback that fails to meet expectations [18], and uncritical or superficial use has been linked to poorer academic performance [8].

2.2. The Turn toward Process and Interaction

Traditional research has explained variance in AI adoption and outcomes through static learner characteristics. The Technology Acceptance Model (TAM) and its extensions identify perceived usefulness, ease of use, and computer self-efficacy as key drivers [19] [20]. Studies have also linked usage to personality traits [21], academic stress [17], time pressure, and trust [22]. While valuable, this trait-centered approach treats the interaction itself as a black box, overlooking the dynamic process of how learners engage with AI in writing tasks.

Fortunately, several new studies endeavors to unpack this black box. Nguyen *et al.* distinguished between linear/passive and interactive/critical collaboration patterns with AI, with the latter yielding better outcomes, regarding engagement quality as a critical moderator [8]. Jin *et al.* demonstrated that AI applications combining self-regulated learning (SRL) principles can enhance motivation and critical thinking [9]. Yao *et al.* explored the metacognitive strategies postgraduates employ when using ChatGPT, highlighting learner's active role [23]. Kim *et al.* systematically analyzed student-AI interaction patterns based on students' AI literacy levels and demonstrated associations between these patterns and academic writing performance [3]. These studies collectively signal a process-oriented turn from asking "whether to use AI" to exploring interaction between users and AI.

2.3. SRL and TAM

Two frameworks are particularly salient for understanding this interaction: Self-

Regulated Learning (SRL) and the Technology Acceptance Model (TAM). SRL theory provides a robust lens for analyzing cognitive and metacognitive processes during learning. It posits that successful learners actively plan, monitor, control, and reflect on their cognition, motivation, and behavior. Research confirms that GenAI can enable SRL by offering immediate feedback and personalized pathways [10]. How students plan their use of AI, monitor its suggestions, evaluate its output, and reflect on the collaboration are typical SRL activities. Differing outcomes from AI use may therefore be rooted in variations in learners' SRL cycles [9]. As a supplement, TAM and extended motivational factors explain initial adoption and continued use. Specifically, self-efficacy, both general and computer-specific, strongly predicts AI adoption and perceived utility [19] [24]. Research has expanded TAM to include social and psychological factors such as social image management and avoidance of academic anxiety, which can motivate performative patterns of use [21].

However, a significant gap persists. While SRL describes the learning process and TAM explains adoption motivations, they are rarely integrated to explain the specific, observable patterns of behavior that emerge when a learner writes with AI. We lack a framework connecting pre-existing motivations and traits (from TAM) to the enactment of specific SRL strategies during the task, which in turn produce divergent psychological and textual outcomes.

2.4. Research Gap and Present Study

This review reveals three interconnected gaps:

First, the literature remains polarized between studies touting AI's benefits and those warning of its dangers, with insufficient focus on the mediating variable of user engagement style. Second, while research on learner traits (via TAM) and learning processes (via SRL) is growing, they operate separately. A unified model is needed to show how traits and motivations translate into real-time engagement patterns. Last, although different styles or patterns have been noted [8], a comprehensive, empirically derived typology of engagement patterns in AI-assisted writing, linked to both antecedents and consequences, is absent.

To address these gaps, this study introduces the concept of AI Engagement Patterns as a core mediating construct. We propose that pre-existing learner factors (e.g., self-efficacy, motivation, anxiety) influence the adoption of a predominant engagement pattern during AI-assisted writing. This pattern represents a specific configuration of SRL strategies in interaction with the technology, which in turn moderates textual output and psychological outcomes, such as authentic versus fragile self-efficacy and strong versus conflicted ownership. We adopt a process-oriented lens, reframing AI as a "cognitive mirror" rather than a mere tool—a reflective surface against which learners calibrate their thinking, strategies, and linguistic choices. The following research questions were formulated:

What distinct engagement patterns emerge when students use AI tools for academic writing tasks?

1) What distinct patterns of engagement do students exhibit when using AI tools for academic writing tasks?

2) How are these engagement patterns associated with students' writing outcomes and psychological experiences (e.g., self-efficacy, sense of ownership, anxiety)?

3) Which learner factors are associated with membership in specific engagement patterns?

By answering these questions, this study develops a coherent typology of engagement grounded in real interaction data to explain divergent outcomes and offer a more nuanced theoretical lens.

3. Method

3.1. Research Context and Participants

This study was conducted in a compulsory "College English" course at a second-tier applied undergraduate university in Jiangsu Province, China. The university offers instruction primarily in Chinese, with English taught as a foreign language subject. Admission is based on students' total scores on the National College Entrance Examination (Gaokao), with no minimum English proficiency requirement for enrollment. Consequently, participants exhibited a wide range of English abilities, which was considered advantageous for capturing diverse patterns of AI interaction.

Participants were recruited through a combination of convenience and purposive sampling. Nine first-year science and engineering students enrolled in a compulsory College English course were invited to participate. To ensure variation in English proficiency, we purposely selected three students from each of three Gaokao English score bands: high (≥128), medium (103 - 122), and low (≤99). For the post-task interviews, we selected six participants to represent all four emergent engagement patterns: two Critical Integrators (P02, P03), one additional Critical Integrator (P08), two Pragmatic Optimizers (P04, P06), and one Architectural Leverager (P07). No Strategic Performers were interviewed because their written logs and AI dialogues already provided rich data, but their textual artifacts were included in the analysis. This selection allowed coverage of each pattern while balancing depth and feasibility.

3.2. Data Collection and Procedure

This study was conducted over a two-week period outside regular class hours. Participants completed all tasks autonomously on their own devices, with remote guidance provided by the researcher.

Pre-task Questionnaire (Week 1, Days 1 - 2). The pre-task questionnaire included a 12-item writing self-efficacy scale adapted from Bandura [25] and Pajares [26], with items rated on a 5-point Likert scale (1 = not confident at all, 5 = completely confident). Sample items: "I can write a clear argumentative essay without AI assistance." AI anxiety was measured with 5 items adapted from Wang *et al.* (2024)

[20], e.g., "I feel anxious when using AI for writing." Positive AI perception was measured with 4 items adapted from Yang *et al.* (2025) [12], e.g., "AI is useful for improving my writing." Scores were averaged for each construct. The baseline self-efficacy questionnaire measured general writing confidence without AI, whereas post-task confidence reports in logs and interviews referred to confidence in revising with AI. We therefore treated them as related but distinct: baseline self-efficacy as a trait-like precursor, and post-task confidence as a task-specific state. Changes in self-efficacy were inferred only when participants explicitly compared their pre-task and post-task confidence or described new capabilities (see **Table 1**).

Table 1. Participant demographics and pre-task characteristics.

Group (by Gaokao score)	Participant ID	Gaokao English	Writing Self-rating	AI Use Frequency	WSE	AIA	AIP
High-proficiency (≥128)	1	129	Excellent	Occasional	4.00	3.40	3.00
	2	128	Good	Rare	3.00	3.00	3.33
	3	133	Good	Rare	2.60	3.20	3.33
	Mean	130.0	—	—	3.20	3.20	3.22
Medium-proficiency (103 - 122)	4	122	Good	Occasional	4.00	3.80	4.67
	5	111	Average	Rare	3.00	2.20	3.67
	6	103	Average	Occasional	3.60	2.80	4.00
	Mean	112.0	—	—	3.53	2.93	4.11
Low-proficiency (≤99)	7	72	Needs Improvement	Frequent	3.40	1.80	2.67
	8	94	Needs Improvement	Rare	4.00	2.20	3.00
	9	99	Good	Occasional	4.00	3.40	4.00
	Mean	88.3	—	—	3.80	2.47	3.22

Note. WSE = Writing Self-Efficacy; AIA = AI Anxiety; AIP = AI Positive Perception. All scales ranged from 1 to 5. Group means are calculated for reference only due to the small sample size.

Task Orientation (Week 1, Day 1). A brief 5-minute online orientation demonstrated how to access DeepSeek and formulate basic prompts (e.g., "check grammar", "improve vocabulary", "evaluate logic"). Participants were reminded that AI was a revision tool, not a ghostwriter.

AI-Assisted Writing Task (Weeks 1 - 2). Participants wrote an argumentative essay (300 - 400 words) on whether traditional academic writing skills remain important in the AI era. The task comprised two stages:

First draft (without AI). Participants wrote an initial draft independently, then completed a writing stage log reporting their satisfaction, confidence, and specific goals for AI consultation.

AI-assisted revision. Participants used DeepSeek to revise their drafts, thinking aloud at key decision points (e.g., accepting, rejecting, or modifying AI sugges-

tions). Think-aloud verbalizations were audio-recorded, and all AI dialogues were automatically logged. After revisions, participants submitted their final draft and a second writing stage log documenting their adoption decisions, rationales, and perceived ownership.

Data Sources and Instruments. Multiple data sources were employed to capture dynamic processes, behavioral patterns, and psychological experiences, aligning with the grounded theory approach:

Writing Stage Logs. Structured logs completed after the first draft and after AI-assisted revision captured: (a) Satisfaction with the draft (1 - 5); (b) Confidence in revising without AI assistance (1 - 5); (c) Specific goals for AI consultation; (d) Expected form of AI help (direct revision, options, or rule explanation); (e) Actual feedback received from AI; (f) Decisions to accept, reject, or modify AI suggestions with rationales; (g) Reflections on confidence changes. These logs provided critical insights into participants' metacognitive awareness and decision-making.

AI Dialogue Transcripts. Complete interaction histories with DeepSeek were automatically recorded and exported as text files. Transcripts documented all user prompts, AI responses, and follow-up queries, revealing questioning strategies, engagement depth, and revision behaviors. These were used in the NVivo three-level coding process.

Think-Aloud Audio Recordings. Participants were instructed to verbalize their reasoning at key decision points during AI-assisted revision (e.g., reading AI suggestions, deciding to accept/reject, rewriting sentences). Audio recordings captured real-time cognitive and emotional responses not fully captured in written logs; they were transcribed and integrated into the qualitative dataset.

Post-task Semi-structured Interviews (within one week after task). Individual interviews (20 - 30 minutes) were conducted with six participants representing the emergent engagement patterns. The interview protocol explored: (a) Rationales for adoption/rejection decisions; (b) Emotional experiences (anxiety, confidence); (c) Perceptions of AI's role; (d) Learning gains; (e) Future AI use strategies. Interviews were audio-recorded and transcribed verbatim, generating approximately 16,000 words of text.

Textual Artifacts. First and final drafts were collected for comparative analysis of textual improvement dimensions (e.g., surface-level enhancement vs. structural reorganization).

Translation and Data Management. To better examine students' interactions with the AI system and their writing processes, think-aloud protocols and post-task interviews were conducted in participants' first language (Chinese) and later translated into English by DeepSeek. To ensure accurate conveyance of participants' meanings between languages, all translated materials were reviewed by an educator who majored in English education. All qualitative data (logs, think-aloud recordings, AI transcripts, interviews) were managed in NVivo 14 for subsequent grounded theory analysis, as detailed in the Data Analysis section.

3.3. Data Analysis

The analysis was initially inductive. SRL and TAM were not used as predetermined coding categories. They were introduced during axial coding as sensitizing concepts to help interpret emerging relationships among codes. For example, when codes related to planning, monitoring, and reflecting clustered together, we drew on SRL to label the category "self-regulated learning strategies". Similarly, codes concerning perceived usefulness, ease of use, and social image were interpreted through TAM. Theoretical saturation is claimed provisionally: no new codes emerged after P08, and P09 produced no new categories, but saturation is always provisional and further cases might refine the typology.

The data analysis proceeded through three phases: open coding, axial coding, and selective coding. Moving between data collection and coding, it followed a grounded theory approach [27] to allow patterns of AI engagement to emerge naturally rather than being imposed by pre-existing frameworks. All qualitative data (writing stage logs, AI dialogue transcripts, think-aloud audio recordings, interview transcripts, and first/final drafts) were imported into NVivo 14 for systematic management and coding.

Open Coding: The author read all materials line-by-line and assigned initial codes to meaningful segments. Codes were kept close to the data, using action-oriented and descriptive labels (e.g., "requesting grammar correction", "rejecting a change to preserve original meaning", "expressing anxiety about knowledge ownership"). This process yielded 65 initial concepts that captured participants' goals, questioning strategies, decision rationales, emotional reactions, and perceived learning outcomes (see **Appendix**).

Notably, the analyst observed that participants with contrasting Gaokao English scores displayed similar behaviors. For instance, P01 (129) and P09 (99) both showed "one-time comprehensive request" and "full acceptance", while P08 (94) and P02 (128) both demonstrated "asking for reasons" and "selective acceptance". This observation challenged the initial assumption that language proficiency would determine AI use patterns, prompting a closer examination of process-oriented codes.

Axial Coding: Axial coding aimed to group the 65 initial concepts into higher-order categories by identifying relationships among them. Using NVivo's hierarchical node structure and matrix coding queries, the researcher merged conceptually similar codes and examined their co-occurrence patterns, which resulted in 14 sub-categories, such as "Goal Orientation", "Query Strategy", and "Type of Learning Gain".

At this stage, a crucial pattern emerged: participants' coding profiles began to cluster not by their proficiency level (high/medium/low) but by the combination of goal orientation, query strategy, and adoption decision. For example, participants who showed "staged questioning" and "selective acceptance" also displayed "high metacognitive reflection" and "long-term capacity orientation". Conversely, those with "one-time request" and "full acceptance" showed low metacognitive

reflection and short-term task orientation. This clustering was independent of Gaokao scores, as evidenced by the distribution across proficiency bands (see Table 2).

Selective Coding: Selective coding integrated the 14 sub-categories into five core categories that together formed a coherent theoretical model:

I. AI Use Behavior Patterns (encompassing goal orientation, query strategy, adoption decision, and tool perception)

II. Psychological Change Trajectories (self-efficacy, ownership, anxiety, and learning gains)

III. Textual Improvement Features (surface-level enhancement vs. structural reorganization)

IV. Learner Cognitive Characteristics (motivation orientation, metacognitive level, language awareness, behavioral initiative)

V. Learner Background Characteristics (self-rated ability, structure dependency, creativity, etc.)

Table 2. NVivo 14 coding frequency and coverage summary.

Node Category	Sub-categories included	Files	References	Coverage (%)	Participants
I. AI Use Behavior Patterns	A1 Goal Orientation; A2 Query Strategy; B1 Adoption Decision; B2 Decision Considerations; D2 Tool Perception	9	142	28.5	P01 - P09
A1: Goal Orientation	Grammar correction; vocabulary upgrading; logical optimization; evidence expansion; sentence variety; holistic polishing	9	34	6.8	P01 - P09
A2: Query Strategy	Staged questioning; one-time request; asking reasons; rule explanation; requesting options; direct revision	9	28	5.6	P01 - P09
B1: Adoption Decision Pattern	Full acceptance; selective acceptance; explicit rejection	9	31	6.2	P01 - P09
B2: Decision Considerations	Critical evaluation; stylistic consistency; proficiency matching; preserving meaning	6	18	3.6	P02, P03, P04, P08
D2: Tool Perception	Assistant; substitute; coach; consultant	9	31	6.2	P01 - P09
II. Psychological Change Trajectories	C1 Self-Efficacy Change; C2 Ownership Change; C3 Anxiety and Concerns; C4 Learning Gain Types	9	118	23.6	P01 - P09
C1: Self-Efficacy Change	Increased self-efficacy; decreased/uneasy self-efficacy	8	32	6.4	P02 - P09
C2: Ownership Change	Increased; decreased; complex/contradictory	9	30	6.0	P01 - P09
C3: Anxiety and Concerns	Tool dependency anxiety; capability replacement concern	7	24	4.8	P03, P05, P06, P07, P09
C4: Learning Gain Types	Sense of learning gain; cognitive gain (rules/structure/expression)	8	32	6.4	P02, P03, P05, P06, P07, P08
III. Textual Improvement Features	D1 Textual Improvement Dimensions	9	48	9.6	P01 - P09

Continued

D1: Textual Improvement Dimensions	Surface-level improvement; logical restructuring; in-depth optimization	9	48	9.6	P01 - P09
IV. Learner Cognitive Characteristics	E1 Motivational Orientation; E2 Metacognitive Level; E3 Language Awareness; E4 Behavioral Initiative	9	96	19.2	P01 - P09
E1: Motivational Orientation	Task completion; learning improvement; efficiency optimization	9	26	5.2	P01 - P09
E2: Metacognitive Level	Strong; weak; moderate	9	25	5.0	P01 - P09
E3: Language Awareness Level	Strong; moderate; weak	9	22	4.4	P01 - P09
E4: Behavioral Initiative	Active exploration; passive acceptance; active control	9	23	4.6	P01 - P09
V. Learner Background Characteristics	F1 Self-Assessment; F2 Motivation Source; F3 Anxiety Tolerance; F4 Time Perspective; F5 Structural Dependency; F6 Expressive Creativity	9	95	19.0	P01 - P09
F1: Self-Assessment of Ability	Weak foundation; confident; moderate	9	16	3.2	P01 - P09
F2: Motivation Source	High extrinsic; high intrinsic; mixed	9	15	3.0	P01 - P09
F3: Anxiety Tolerance	Low; high	6	12	2.4	P02, P03, P04, P05, P07, P08
F4: Time Perspective	Short-term task; long-term capability; pragmatic	8	18	3.6	P01 - P09
F5: Structural Dependency	Strong; moderate; strong independence	6	16	3.2	P02, P03, P04, P05, P07, P08
F6: Expressive Creativity	Low; high	8	18	3.6	P01 - P09
Total	—	9	499	100.0	P01 - P09

Note. NVivo 14 output. Files = number of participant files containing the node; References = number of coded segments; Coverage = percentage of total coded references.

Through constant comparative analysis across the nine participants, four stable and distinct engagement patterns emerged. These patterns were named based on their dominant behavioral and psychological profiles:

Strategic Performer (P01, P09)

Practical Optimizer (P04, P06)

Architectural Leverager (P05, P07)

Critical Integrator (P02, P03, P08)

Pattern assignment was based on observable behavioral criteria derived from process data, independent of psychological outcomes. Criteria included: (a) Goal specificity (broad vs. specific requests); (b) Query strategy (one-time vs. staged vs. metacognitive questioning); (c) Adoption decisions (full acceptance vs. selective acceptance vs. critical rejection); (d) Tool perception (substitute vs. assistant vs. consultant). For example, P06 was classified as a Pragmatic Optimizer despite asking for explanations, because his requests remained bounded to surface-level features (vocabulary, grammar) and he explicitly rejected structural changes. His explanation-seeking was instrumental to surface optimization, not indicative of crit-

ical integration, which requires questioning underlying logic and evaluating suggestions against personal standards. Overlapping cases were resolved by identifying the dominant pattern across the entire process, not isolated instances. This cross-proficiency distribution confirmed that engagement pattern was the key explanatory variable for writing outcomes and psychological experiences.

3.4. Theoretical Saturation and Trustworthiness

To ensure the credibility of the qualitative findings, we employed multiple strategies, including triangulation, inter-coder reliability checks, member checking, and peer debriefing. Figure 1 presents the triangulation and trustworthiness flowchart. Data from six sources, *i.e.* pre-task questionnaires, writing stage logs, AI dialogue transcripts, think-aloud recordings, post-task interviews, and first/final drafts, were integrated during the coding process. This multi-source triangulation allowed us to cross-verify behavioral, textual, and psychological evidence, thereby strengthening the validity of the four emergent engagement patterns (see Table 3).

Table 3. Triangulation matrix across data sources and engagement patterns.

Data Source	Strategic Performer (P01, P09)	Pragmatic Optimizer (P04, P06)	Architectural Leverager (P05, P07)	Critical Integrator (P02, P03, P08)
Process logs	Brief reflections; task-completion focus	Practical reflections; tool-control focus	Anxious reflections; capability-gap focus	In-depth reflections; learning-gain focus
AI dialogues	Direct requests; full acceptance	Specific requests; selective acceptance	Holistic requests; acceptance of framework	Staged requests; asking for reasons
Textual comparison	Stylistic rupture; linguistic leap	Framework retained; vocabulary upgraded	Structure reshaped; quality leap	Style consistent; in-depth optimization
Interviews/ reflections	Contradictory ownership; fragile efficacy	Strong control; stable efficacy	Anxiety and hope coexisting; fluctuating efficacy	Rational cognition; authentic efficacy
Psychometric measures	High social desirability; low process investment	High tool control; moderate cognitive investment	High dependency anxiety; high cognitive need	High meta-cognition; high active learning
Convergent finding	AI as filter; efficacy externally derived	AI as makeup mirror; efficacy tool-based	AI as X-ray; efficacy ambivalent	AI as calibration instrument; efficacy authentic

Note. This matrix demonstrates how multiple data sources converged to support the four-pattern typology and the interpretation of AI as a cognitive mirror.

Theoretical saturation was achieved after analyzing the eighth participant (P08); the ninth participant (P09) did not generate any new codes or categories. Inter-coder reliability was established by having two coders independently code 25% of the data, yielding a Cohen's Kappa of 0.84. All discrepancies were resolved through discussion. Member checking was conducted by returning summarized interpretations to selected participants, who confirmed that the descriptions accurately reflected their experiences. Peer debriefing with two colleagues external to the study provided additional checks on the coding framework and interpretive claims. As shown in Figure 1, these procedures collectively ensured that the typology was grounded in the data instead of an artifact of researcher bias.

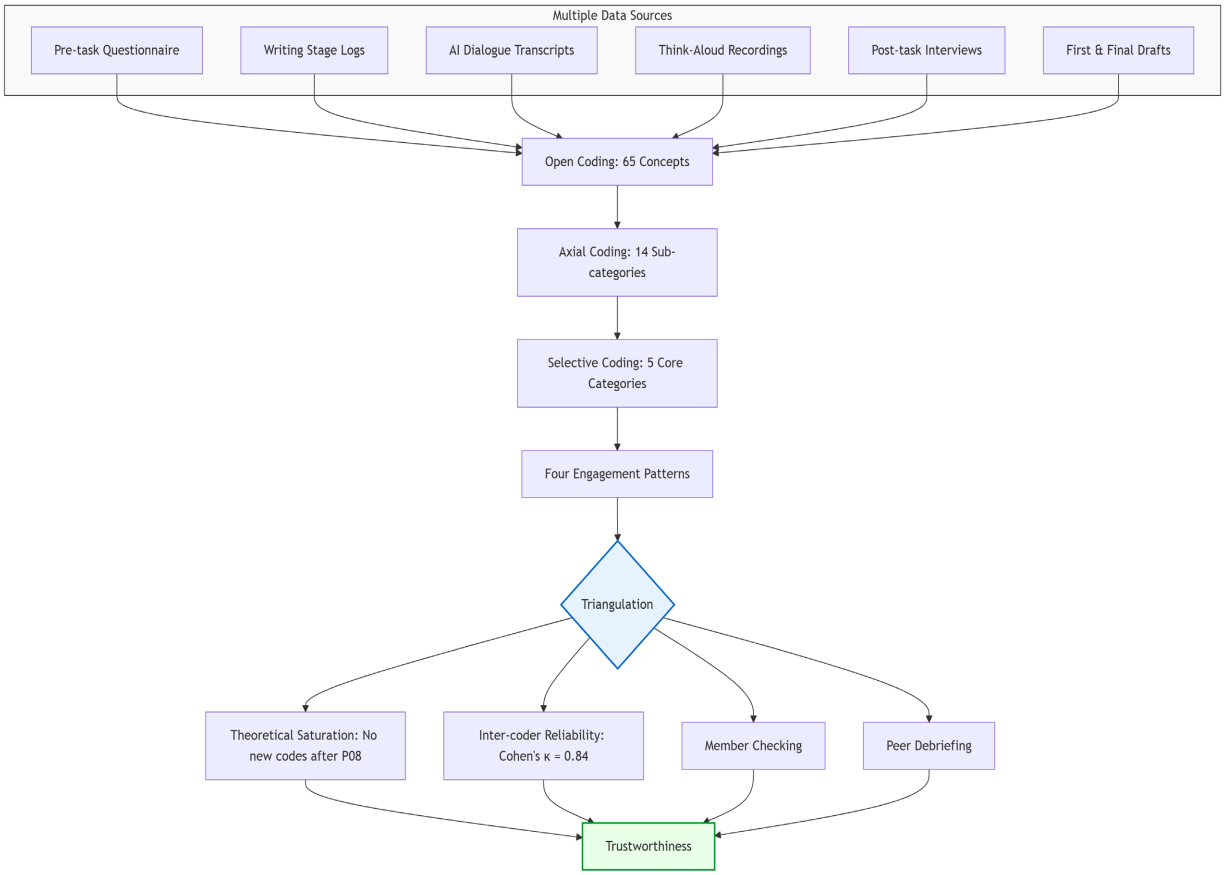


Figure 1. Triangulation and trustworthiness flowchart.

4. Results

The analysis revealed four distinct engagement patterns that impact students' writing outcomes and psychological experiences, which didn't align with participants' language proficiency levels; rather, they reflected how students set goals, queried the AI, processed feedback, and managed their emotions during the revision process (see Table 4). Each pattern is presented Below through the in-depth portraits of representative cases, with supporting evidence from other participants.

Table 4. Cross-case comparison of four engagement patterns.

Dimension	Strategic Performer (SP)	Pragmatic Optimizer (PO)	Architectural Leverager (AL)	Critical Integrator (CI)
Primary goal	Efficient task completion	Surface-level optimization	Structural rescue	Capacity development
Role of AI	Authoritative tool/substitute	Precision tool (grammar & vocabulary)	Cognitive scaffold	Cognitive mirror/ consultant
Query strategy	One-time, broad request	Specific, bounded requests	Holistic polishing request	Staged, metacognitive questioning
Adoption decision	Full acceptance	Selective acceptance (surface only)	Full acceptance of structural revisions	Critical, selective adoption with reasons
Textual improvement	Stylistic rupture; linguistic leap	Vocabulary upgraded; framework retained	Structure reshaped; quality leap	Balanced improvement; style consistent
Self-efficacy change	Inflated, externally derived	Stable, tool-based	Fragile, ambivalent	Authentic, learning-based
Ownership perception	Contradictory/ rationalized	Strong control	Conflicted/ anxious	Rational, differentiated
Anxiety type	Low anxiety, shallow engagement	Low anxiety, high control	High dependency & capability anxiety	Low anxiety, high metacognitive regulation
Learning gain	Limited	Lexical resources/ templates	Structural schema (what a good essay looks like)	Strategies and self-regulation skills
Metacognitive level	Low	Moderate	Moderate (reactive)	High
SRL cycle engagement	Minimal (outsourced)	Partial (surface monitoring)	External scaffolding dependent	Full cycle (plan, monitor, evaluate, reflect)
Typical participants	P01, P09	P04, P06	P05, P07	P02, P03, P08

Note. SP = Strategic Performer; PO = Pragmatic Optimizer; AL = Architectural Leverager; CI = Critical Integrator. This table synthesizes cross-case evidence from process logs, AI dialogue transcripts, think-aloud recordings, interviews, and textual artifacts.

4.1. Strategic Performers

Strategic Performers approached the AI-assisted writing task with a primary goal of completing the task efficiently with minimal personal cognitive effort. They issued broad or one-time requests, and accepted AI revisions wholesale without critical evaluation and their final drafts often showed dramatic linguistic enhancement but a marked stylistic break from their original writing. AI is treated not as

a collaborator but an absolutely correct and perfect robot tool. Psychologically, they displayed contradictory or rationalized ownership and a self-efficacy that appeared inflated.

Case P01 (Gaokao English: 129; self-rated writing: good; pre-task self-efficacy: 4.0; AI anxiety: 3.4; positive AI perception: 3.0) was a high-proficiency student who, despite strong language ability, exhibited a strategic and perfunctory approach to the task. He showed a strong willingness and enthusiasm when being invited to participate in the project. However, his initial draft was hastily written and incomplete, requiring several reminders to submit. In his interactions with DeepSeek, P01 posed a series of strategic but surface-level requests: "Check grammar and spelling errors", "Help me extend this sentence to make it richer", "Use a more academic tone", and finally, "Polish the last paragraph to make it more concise and highlight the main idea". Each request was fulfilled by AI, and P01 accepted all revisions without questioning or seeking explanations. His final draft was transformed into a polished, academic essay that no longer reflected his own voice or original expression. His log entries were minimal, focusing only on the fact that changes were made, with no reflection on the learning process. When asked about ownership, P01 stated, "The ideas are mine, but most of the expressions are AI's." This statement reflects rationalization rather than accurate differentiation. P01's minimal engagement and wholesale acceptance suggest low ownership despite his claim.

Case P09 (Gaokao English: 99; self-rated writing: needs improvement; pre-task self-efficacy: 2.6; AI anxiety: 3.2; positive AI perception: 3.33) provides a complementary portrait. Although his initial draft contained errors such as "In first" and "The second aspects", he expressed high satisfaction with the draft (4/5) and moderate confidence (3/5). His main concerns were logical structure, grammar, and vocabulary. In his log, he stated his goal: "Check for grammar errors and logical structure." His expectation was for AI to "directly revise sentences and explain the modifications". After receiving AI feedback, he accepted all revisions, explaining, "I accepted all modifications because AI expressed my intended meaning more accurately." His final draft was essentially the AI's version, with only minor personal adjustments. In his post-task reflection, P09 reported increased confidence, stating, "I am more confident because AI pointed out my errors and gave me suggestions." He also claimed enhanced ownership: "The main idea is still mine; AI was only a tool." However, this ownership claim is questionable given that the final text was largely AI-generated. His self-efficacy gain is externally derived and fragile.

4.2. Pragmatic Optimizers

In this pattern, participants' interactions were characterized by specific, bounded requests and a clear boundary between acceptable (surface) and unacceptable (deep) AI intervention. They set specific, limited goals—correcting grammar, upgrading vocabulary, or expanding word count—and actively rejected suggestions

that threatened their original meaning or structural framework. Their final drafts showed improved language but retained the original logical organization and argument depth. Psychologically, they showed low anxiety about dependency and stable self-efficacy rooted in tool mastery.

Case P04 (Gaokao English: 122; self-rated writing: average; pre-task self-efficacy: 4.0; AI anxiety: 3.4; positive AI perception: 4.0) exemplifies this pattern. His initial draft had a clear structure but suffered from inaccurate word choices and simple sentence structures. In his dialogue with AI, P04 proceeded systematically: first, he asked for spelling and grammar corrections; second, he requested vocabulary upgrades; third, he asked AI to check logical coherence and expand content. When AI provided a deeply revised version that reorganized his arguments and added a new paragraph, P04 did not accept it. Instead, he asked, "What is the function of the fourth paragraph? Does it affect the logic? Should I delete it?" He also requested that AI replace several advanced words with simpler alternatives that better matched his intended meaning. His final draft preserved the original "student-school-government" parallel structure while incorporating improved vocabulary and corrected grammar. In his log, P04 wrote, "I rejected AI's deep revisions because they changed my original meaning and were not easy to read." His confidence remained high throughout, and he reported that the process made him "more aware of how to polish an essay without losing my own voice". His self-efficacy was stable and authentic because it was based on his successful control of the tool, not on the tool's output.

Case P06 (Gaokao English: 103; self-rated writing: average; pre-task self-efficacy: 3.8; AI anxiety: 2.0; positive AI perception: 4.0) further illustrates the pragmatic optimizer's priorities. His initial draft was short and simple. He asked AI to "expand the essay to about 320 words, correct errors, optimize structure, enrich vocabulary, and strengthen arguments". AI responded with a fully rewritten, well-structured essay. P06 then asked AI to explain the reasons for each modification. After reviewing the explanations, he selectively adopted AI's vocabulary and examples but ignored the suggested logical connectors and forgot to correct basic grammar errors such as "broaden us horizons". In his log, he admitted, "At that time, I focused on improving good words and sentences, and later I forgot about the basic corrections." His final draft showed noticeable lexical improvement but retained a simple logical structure and even some of the original grammatical errors. In the interview, P06 explained that his writing ability had improved mainly in "finding and using advanced vocabulary", and that he felt more confident because he now had "more templates and materials". However, he also noted that the abundance of new words made some sentences difficult to read. His self-efficacy increased, but it was tied to the accumulation of lexical resources rather than to a deeper understanding of writing as a cognitive process.

4.3. Architectural Leveragers

With lower initial confidence and weaker linguistic foundations, participants in

this pattern relied heavily on AI to restructure their essays at the logical and organizational levels. They used AI as a crutch to overcome fundamental structural deficits and accepted AI's structural blueprints wholesale or with minimal modification, resulting in dramatic improvements in text quality but triggering significant anxiety about ownership and capability. Their learning gains are real but largely confined to recognizing what a good essay looks like, rather than acquiring the ability to produce one independently.

Case P07 (Gaokao English: 72; self-rated writing: needs improvement; pre-task self-efficacy: 3.2; AI anxiety: 3.0; positive AI perception: 3.33) is the most striking example. His initial draft was full of grammatical errors, Chinese-English expressions, and fragmented logic. In his log, he rated his satisfaction as 3/5 and his confidence in independent revision as 2/5. His main concerns were "grammar, spelling, and persuasiveness". In his first interaction with AI, he asked, "Please find and correct the grammatical errors in my essay." AI provided a detailed correction. He then asked, "If you were to polish the essay, how would you do it?" AI returned two versions, one of which was a fully restructured, logically coherent argument. P07 accepted this version almost entirely. He later explained in the interview, "AI's logic and language were better than mine, and its reasons for the changes convinced me." His final draft bore little resemblance to his initial draft: it had a clear three-part argument, sophisticated transitions, and a compelling conclusion. However, this dramatic improvement came at a psychological cost. In the interview, P07 expressed deep anxiety: "I always feel that the knowledge is not from my own mind. The ability is my existing knowledge; a tool is just a helper. What I can do with a tool is not what I can do independently." Although worried that the final essay "was not something I could have written myself", he acknowledged learning gains: "I learned how a rigorous argumentative essay should be organized." His self-efficacy was ambivalent, more confident about the final product but less confident about his own ability without AI. His ownership was conflicted: he knew the ideas were his, but the expression and structure were largely AI's.

Case P05 (Gaokao English: 111; self-rated writing: average; pre-task self-efficacy: 3.0; AI anxiety: 2.2; positive AI perception: 3.67) showed a similar pattern, though with less dramatic improvement. His initial draft was simple and non-idiomatic. He asked AI to "modify sentences, optimize words, and improve paragraph logic". He accepted AI's structural changes, including the use of "First, Second, Third" connectors. In his log, he wrote, "I accepted AI's modifications to sentence structure because they were more authentic. I rejected some complex words because they were less concise." His final draft showed improved organization but still retained awkward phrases such as "I have three main reasons to support my view", indicating limited internalization of the structural principles. In his post-task reflection, he reported increased confidence because "AI's solutions were better and benefited me a lot". However, he also expressed unease: "AI is more advanced than me; I worry that the revised essay is not something I could

achieve on my own." His ownership was enhanced in a compensatory way: "The initial draft was mine, and AI was like an assistant. With an assistant, the essay is more complete." This rationalization allowed him to claim ownership while acknowledging dependence.

4.4. Critical Integrators

Critical Integrators engaged with AI in a phased, metacognitive manner. They set clear sub-goals, asked for explanations, requested options, and critically evaluated AI suggestions against their own intentions and stylistic preferences. Their final drafts showed balanced improvement in language and logic while maintaining stylistic consistency. Psychologically, they experienced authentic self-efficacy gains, rational ownership perceptions, and low dependency anxiety. They treated AI as a cognitive mirror, using it to calibrate their own thinking and expression rather than to replace it.

Case P02 (Gaokao English: 128; self-rated writing: good; pre-task self-efficacy: 3.4; AI anxiety: 4.0; positive AI perception: 4.33) provides the richest portrait. His initial draft was carefully written. In his log, he rated satisfaction 3.5/5 and confidence 3/5. His main concerns were "whether the argument transitions follow a logical order and whether spelling and word choice are accurate". He then designed a four-stage plan for AI consultation: (1) Check grammar and spelling; (2) Examine the logical order of arguments; (3) Improve idiomatic expression; (4) Polish the conclusion to be concise and highlight the main idea. For each stage, he specified the expected form of help: direct corrections with explanations, logical reorganization with rationale, alternative expressions to choose from, and a revised conclusion with justification. In his interaction, he did not simply accept AI's output. For example, when AI suggested a more sophisticated expression for "人类几千年文明智慧的积累 (The accumulation of human civilization's wisdom over thousands of years)", P02 rejected it, explaining in his log: "I did not modify this part because the AI's version was too advanced and did not match my overall writing level." He also asked AI to explain why certain changes were better, and he requested multiple options before making a decision. His final draft retained his original ideas and personal style while incorporating improved vocabulary, corrected grammar, and more logical transitions. In his post-task reflection, P02 reported increased confidence: "I feel more confident because I combined AI with my own thinking and improved my judgment." P02 also stated, "The ideas are mine, but most of the expressions are AI's." In contrast to P01, this statement reflects accurate differentiation: P02 selectively adopted suggestions, rejected those that did not match his level, and maintained stylistic consistency. His active regulation suggests high ownership. Self-efficacy changes were interpreted cautiously; perceived confidence gains were not equated with demonstrated competence. Only when participants demonstrated understanding of revisions (e.g., explaining rules, applying to new contexts) did we infer authentic self-efficacy. P07's increased confidence about the final product but anxiety about independent ability

was coded as ambivalent efficacy.

Case P03 (Gaokao English: 133; self-rated writing: good; pre-task self-efficacy: 3.4; AI anxiety: 2.2; positive AI perception: 2.67) exhibited a similar critical approach. His initial draft was already high quality. In his dialogue, he asked AI not only to revise but also to explain: "What is good about your revision?" He requested that AI provide new arguments for his consideration rather than directly generating English text. He then selectively incorporated suggestions that he judged valuable. His final draft was polished, logically tight, and stylistically consistent. In his log, he noted that the decision process made him "more confident" because he learned "how to organize an essay to make the argument clearer". His ownership was clear: "The ideas are mine; AI helped with expression." His self-efficacy improved through genuine learning.

Case P08 (Gaokao English: 94; self-rated writing: average; pre-task self-efficacy: 3.6; AI anxiety: 2.8; positive AI perception: 3.67) demonstrates that even a student with moderate proficiency can become a Critical Integrator. His initial draft contained numerous grammatical errors and inappropriate word choices. However, his interaction with AI was characterized by persistent questioning. He asked AI to correct grammar and spelling, but he also asked for explanations of rules: "Isn't 'although' used for contrast? Why is there no 'but'?" He asked for alternative expressions for "相辅相成 (complement each other)" and selected the one that best fit his level. He rejected AI's advanced revisions that changed his original meaning, stating, "I want to keep my own voice." His final draft showed improved grammar and expression while preserving his original ideas and style. In his post-task reflection, he reported increased confidence because he "learned many collocations and sentence structures". His ownership decreased rationally: "AI provided many ideas I couldn't have thought of, so the essay is partly AI's." But his self-efficacy was authentic because he had actively engaged with and understood the revisions.

4.5. Cross-Pattern Synthesis

Across the four patterns, the decisive factor was not language proficiency but the engagement pattern—the combination of goals, query strategies, adoption decisions, and psychological regulation. Students with similar Gaokao scores ended up in different patterns. Conversely, students with vastly different proficiency levels sometimes shared the same pattern (see Table 4).

The psychological outcomes varied systematically:

Self-efficacy: Strategic Performers showed inflated, externally derived efficacy; Pragmatic Optimizers displayed stable, tool-based efficacy; Architectural Leveragers experienced fragile, ambivalent efficacy; Critical Integrators achieved authentic, learning-based efficacy.

Ownership: Strategic Performers reported contradictory or rationalized ownership; Pragmatic Optimizers maintained strong ownership through selective adoption; Architectural Leveragers expressed conflicted ownership; Critical Inte-

grators held rational, differentiated ownership.

Anxiety: Strategic Performers showed low anxiety but shallow engagement; Pragmatic Optimizers had low anxiety and high control; Architectural Leveragers experienced high dependency and capability anxiety; Critical Integrators had low anxiety and high metacognitive regulation.

This study provides an exploratory typology of engagement patterns in AI-assisted writing. The findings suggest that engagement patterns, rather than language proficiency alone, are associated with different writing outcomes and psychological experiences. However, cross-proficiency pattern membership does not establish that proficiency has no influence on outcomes; proficiency may still shape outcomes through other pathways not examined here. Future research should test these associations with larger samples and experimental designs.

5. Discussion

5.1. Theoretical Dialogue

The four engagement patterns identified in this study demonstrate varying levels of metacognitive strategy use and motivational regulation, aligning closely with self-regulated learning (SRL) theory [28]. Critical Integrators exhibited the most mature SRL cycle, encompassing planning (e.g., staged goals), monitoring (e.g., evaluating AI suggestions), evaluating (e.g., distinguishing their own contributions from AI's), and reflecting (e.g., considering future use). In contrast, Strategic Performers largely outsourced their SRL processes to the AI, showing minimal planning, monitoring, or reflection. Pragmatic Optimizers displayed selective SRL, focusing on surface-level monitoring while avoiding deeper cognitive engagement. Architectural Leveragers relied on external scaffolding to complete the SRL cycle, with their regulation heavily dependent on AI's structural input. These differences echo recent findings that self-regulation and critical thinking are stronger predictors of effective generative AI use than general writing competence [9]. The typology thus offers a behavioral specification of SRL in AI-assisted writing contexts.

Beyond the traditional determinants of perceived usefulness and ease of use, our findings reveal deeper psychological variables that shape how students engage with AI. Social image management emerged as a key motivator for Strategic Performers, who sought to produce acceptable texts with minimal effort, consistent with research linking social image to AI usage [29]. Cognitive conflict tolerance distinguished Architectural Leveragers and Critical Integrators: the former experienced high anxiety when confronting the gap between their ability and AI output, while the latter tolerated and regulated this conflict through metacognitive questioning. This extends the Technology Acceptance Model [30]by highlighting emotional and identity-related factors—such as fear of incompetence and desire for social approval—as critical moderators of AI adoption and sustained use.

We propose the metaphor of AI as a "cognitive mirror" to capture how its effects depend not on students' pre-existing proficiency, but on their willingness to

"gaze into the mirror" and the depth of that gaze. For Strategic Performers, AI acts as a filter, projecting a polished image while obscuring real competence. For Pragmatic Optimizers, it is a makeup mirror for surface refinement. For Architectural Leveragers, it serves as an X-ray, revealing structural flaws but also inducing anxiety. For Critical Integrators, it functions as a calibration instrument for precise self-adjustment. This metaphor aligns with the view that AI's impact is mediated by learners' self-regulated engagement [9] [10]. It shifts the focus from the tool itself to the learner's metacognitive stance, offering a nuanced framework for understanding divergent outcomes.

5.2. Pedagogical Implications

Our findings caution against uniformly promoting AI tools in writing instruction. A blanket approach may reinforce shallow learning for Strategic Performers and entrench Pragmatic Optimizers in their comfort zones. Prior research has similarly warned that uncritical AI use can erode critical thinking and foster dependency [7] [16]. Therefore, pedagogical interventions must be differentiated according to students' engagement patterns, rather than assuming that AI benefits all learners equally.

For Strategic Performers, instructors should design tasks that transform social motives into genuine learning goals, such as requiring students to defend their AI-assisted revisions orally. For Pragmatic Optimizers, tasks should force engagement with logical and argumentative depth, for example by asking AI to identify the weakest logical links and requiring students to rewrite those sections. Architectural Leveragers need metacognitive coaching to convert anxiety into a growth roadmap, gradually reducing reliance on AI scaffolds. Critical Integrators can be empowered to share their strategies with peers, fostering a classroom culture of critical collaboration. These recommendations resonate with calls for SRL-based AI integration and highlight the need for differentiated instructional support [9] [10].

5.3. Limitations and Future Directions

Several limitations should be acknowledged. First, the sample size was small (N = 9), limiting generalizability. Second, Gaokao English scores may not fully reflect actual writing proficiency, as students' performance can vary across contexts. Third, the study was conducted in a specific cultural and educational context (a Chinese university), which may influence AI engagement patterns. Fourth, long-term effects were not tracked; future research should employ longitudinal designs. Fifth, self-reported data in questionnaires may be subject to social desirability bias. Future studies should validate the typology with larger and more diverse samples, incorporate objective writing assessments, and explore how engagement patterns evolve over time. Additionally, research should examine the effectiveness of targeted interventions in shifting students toward more critical engagement patterns [8] [12].

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Conflicts of Interest

The author declares no conflicts of interest.

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Appendix

Open Coding: Initial Concepts, Participants, Frequency, and Axial Categories

	Initial Concept	Participants	F	Axial Category
1	Grammar error correction needs	P02, P03, P04, P06, P07, P08	6	A1: Goal Orientation
2	Vocabulary upgrading needs	P02, P04, P06, P08	4	A1: Goal Orientation
3	Logical structure optimization needs	P02, P03, P05, P07	4	A1: Goal Orientation
4	Evidence expansion needs	P03, P06	2	A1: Goal Orientation
5	Sentence variety enrichment needs	P06	1	A1: Goal Orientation
6	Holistic polishing request	P01, P07, P09	3	A1: Goal Orientation
7	Staged questioning strategy	P02, P03	2	A2: Query Strategy
8	One-time comprehensive request	P01, P09	2	A2: Query Strategy
9	Asking for reasons for modifications	P03, P08	2	A2: Query Strategy
10	Requesting rule explanations	P05, P08	2	A2: Query Strategy
11	Requesting options	P02, P03	2	A2: Query Strategy
12	Requesting direct revision	P04, P06	2	A2: Query Strategy
13	Full acceptance of revisions	P01, P05, P07, P08, P09	5	B1: Adoption Decision Pattern
14	Selective acceptance	P02, P03, P04	3	B1: Adoption Decision Pattern
15	Explicit rejection of revisions	P02, P03, P04, P08	4	B1: Adoption Decision Pattern
16	Critical evaluation	P02, P03, P08	3	B2: Decision Considerations
17	Consideration of stylistic consistency	P02, P08	2	B2: Decision Considerations
18	Consideration of proficiency matching	P02	1	B2: Decision Considerations
19	Consideration of preserving original meaning	P04, P08	2	B2: Decision Considerations
20	Increased self-efficacy	P02, P03, P04, P06, P07, P08	6	C1: Self-Efficacy Change
21	Decreased self-efficacy/unease	P05, P07, P09	3	C1: Self-Efficacy Change
22	Increased sense of ownership	P04, P05, P06, P09	4	C2: Ownership Change
23	Decreased sense of ownership	P02, P08	2	C2: Ownership Change
24	Complex/contradictory sense of ownership	P01, P07	2	C2: Ownership Change
25	Tool dependency anxiety	P03, P05, P06, P07	4	C3: Anxiety and Concerns
26	Concern about capability replacement	P07, P09	2	C3: Anxiety and Concerns
27	Sense of learning gain	P02, P03, P06, P07, P08	5	C4: Learning Gain Types
28	Cognitive gain (rules)	P08	1	C4: Learning Gain Types
29	Cognitive gain (structure)	P05, P07	2	C4: Learning Gain Types
30	Cognitive gain (expression)	P02, P06, P08	3	C4: Learning Gain Types
31	Surface-level textual improvement	P04, P06	2	D1: Textual Improvement Dimensions
32	Logical restructuring of text	P05, P07, P09	3	D1: Textual Improvement Dimensions
33	In-depth textual optimization	P02, P03	2	D1: Textual Improvement Dimensions
34	Tool positioned as assistant	P05, P06, P08	3	D2: Tool Perception

Continued

35	Tool positioned as substitute	P01, P09 (implied)	2	D2: Tool Perception
36	Tool positioned as coach	P07	1	D2: Tool Perception
37	Tool positioned as consultant	P02, P03	2	D2: Tool Perception
38	Task completion orientation	P01, P09	2	E1: Motivational Orientation
39	Learning improvement orientation	P02, P03, P07, P08	4	E1: Motivational Orientation
40	Efficiency optimization orientation	P04, P06	2	E1: Motivational Orientation
41	Strong metacognitive reflection	P02, P03, P08	3	E2: Metacognitive Level
42	Weak metacognitive reflection	P01, P09	2	E2: Metacognitive Level
43	Moderate metacognitive reflection	P04, P05, P06, P07	4	E2: Metacognitive Level
44	Strong language awareness	P02, P03, P08	3	E3: Language Awareness Level
45	Moderate language awareness	P04, P06	2	E3: Language Awareness Level
46	Weak language awareness	P05, P07, P09	3	E3: Language Awareness Level
47	Active exploration behavior	P02, P03, P08	3	E4: Behavioral Initiative
48	Passive acceptance behavior	P01, P05, P07, P09	4	E4: Behavioral Initiative
49	Active control behavior	P04	1	E4: Behavioral Initiative
50	Acknowledgment of weak foundation	P05, P07	2	F1: Self-Assessment of Ability
51	Confident expression of ability	P02, P04	2	F1: Self-Assessment of Ability
52	Moderate self-rated ability	P03, P06, P08	3	F1: Self-Assessment of Ability
53	High extrinsic motivation	P01, P09	2	F2: Motivation Source
54	High intrinsic motivation	P02, P03, P07, P08	4	F2: Motivation Source
55	Mixed motivation	P04, P05, P06	3	F2: Motivation Source
56	Low anxiety tolerance	P05, P07	2	F3: Anxiety Tolerance
57	High anxiety tolerance	P02, P03, P04, P08	4	F3: Anxiety Tolerance
58	Short-term task perspective	P01, P09	2	F4: Time Perspective
59	Long-term capability perspective	P02, P03, P07, P08	4	F4: Time Perspective
60	Pragmatic perspective	P04, P06	2	F4: Time Perspective
61	Strong structural dependency	P05, P07	2	F5: Structural Dependency
62	Moderate structural independence	P02, P03, P04	3	F5: Structural Dependency
63	Strong structural independence	P08	1	F5: Structural Dependency
64	Low expressive creativity	P01, P05, P07, P09	4	F6: Expressive Creativity
65	High expressive creativity	P02, P03, P04, P08	4	F6: Expressive Creativity

Note: P01 - P09 refer to individual participants. Frequency indicates the number of participants exhibiting the concept. Axial categories correspond to the 14 sub-categories derived during the second phase of coding.