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Journal of Qualitative Research in Education

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Article

The Lived Experience of Perceived AI Risks in Language Learning: A Phenomenological Inquiry into University Students' Perspectives

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Received: 11 December 2025; **Revised:** 30 December 2025; **Accepted:** 21 January 2026; **Published:** 28 February 2026

Abstract: In this study, interpretive phenomenology was adopted to explore how university students make sense of AI risks when using AI in language learning contexts. Eighteen undergraduate students were interviewed individually, with participants also completing experience journals during the two-week interview period. Three dialectical themes were found after analyzing all interview transcripts and journals: (1) "the panic of too much convenience." Students felt torn between the lure of being efficient and losing control, oscillating between saving time vs. taking shortcuts to learn, feeling empowered vs. dependent, affirming vs. losing authorship; (2) "hallucination" and "gatekeeper": AI's output had "hallucinations," which destroyed trust; students switched roles from producer to proofreader, experiencing physical anxiety about academic integrity; (3) "Is it still my learning?" cognitive offloading caused metacognitive doubt whether deep learning still took place once there were no longer any desirable difficulties. Our results suggest that risk does not belong to AI itself but rather is a meaningful world created by users under certain conditions. Instead of simply accepting/rejecting AI, students have developed context-based self-regulation strategies against AI risks. Our study tries to go beyond the limits of stage models for technology adoption and offers a phenomenological account of what it feels like to be a learner living in technologically mediated times. We argue here for turning the conflict into teaching moments so as to nurture critically minded AI literacies.

Keywords: Educational Phenomenology; Large Language Model; Sense of Risk; Feeling of Life; Language Learning; Sense of Self-Efficacy; Metacognitive Anxiety; Qualitative Metasynthesis

1. Introduction

Large language models are reshaping the learning ecology of higher education at unprecedented speed. This transformation is particularly evident in language learning domains. Generative AI tools such as ChatGPT have shifted from peripheral auxiliary resources to ubiquitous "invisible participants" in daily writing practices. Contemporary university students stand at the forefront of this technological revolution. They are both beneficiaries of AI-enabled education and the most direct bearers of technological risks [1]. They also serve as primary meaning-makers in this context. AI intervention occurs in the private spaces of academic writing. Consider the late-night thesis revisions, the repeated deliberations over English expressions, the final hesitations before clicking the submit button. These moments reveal something crucial. AI changes not only the methods of text production but also touches the fundamental anxieties of learners about capability, identity, and academic integrity. However, existing research mostly focuses on AI's technical efficacy or students' attitude assessments regarding "usefulness" and "ease of use." Few studies delve into the lived world of learners. Researchers rarely listen to the genuine confusion, struggles, and meaning negotiations students experience when using AI [2]. This neglect of the experiential dimension leaves our understanding superficial. We still lack deep insights into core questions: "How do students perceive risks?" and "How do risk experiences shape learning practices?" Traditional technology acceptance models simplify learners' decision-making processes into rational calculations. Students supposedly weigh benefits against costs, then choose adoption or rejection. But this variable-centered thinking obscures the complexity of risk as a "lived experience." Risk is not merely an objective probability of threat. Rather, learners construct it as a meaningful world through bodily perceptions, emotional fluctuations, and reflective thinking within specific contexts [3–5]. Consider an English learner using AI to generate academic argumentation. She may simultaneously experience the pleasure of time savings, doubts about machine accuracy, a sense of loss as authorship becomes diluted, and fear of being scrutinized by academic norms. These interwoven emotional and cognitive states constitute a dynamic meaning field full of tension. They cannot be reduced to several scores on a scale. Educational phenomenology offers an alternative perspective. It calls researchers to "return to things themselves." We must understand how technology is experienced, interpreted, and integrated into daily learning practices within learners' lived worlds [6–8].

2. Literature Review

2.1. Functional Paradigm in AI and Language Learning Research: Efficacy, Gains, and Acceptance Models

Existing scholarship demonstrates that generative AI fundamentally reshapes the technological ecosystem of language pedagogy. From a functional empowerment perspective, AI chatbots deliver individualized vocabulary scaffolding, attenuate foreign language anxiety, sustain interactive engagement, and enhance cross-cultural competence through gamified interfaces. Systematic reviews of Intelligent Tutoring Systems (ITS) confirm their pedagogical effectiveness in instructional design and learning facilitation, their capacity to nurture learner autonomy and competency development, and their contribution to learner well-being within Self-Determination Theory's social-emotional learning framework [9]. However, these investigations predominantly foreground technological efficacy and predictive modeling of learning strategies, while marginalizing learners' phenomenological dimensions—their subjective interpretations, meaning-making processes, and existential struggles embedded in AI-mediated practices [10].

2.2. Critical Gaps: Competency Metrics versus Lived Literacy Experiences

Current scholarship exhibits three salient limitations. First, while researchers examine university students' AI literacy status and developmental pathways, these inquiries remain confined to competency-based frameworks, neglecting how students existentially inhabit and embody these emerging capabilities in everyday academic practices [11]. Second, although correlations between foreign language speaking anxiety and AI deployment have been documented [6], granular investigations into affective textures and emotional phenomenology across varied risk dimensions—academic jeopardy, cognitive dependency, identity destabilization, and ethical conflicts—remain conspicuously absent [12]. Third, prevailing research constructs learners as rational utility-maximizing agents exercising binary adoption choices, thereby obscuring the ongoing dialectical tensions between AI-enabled assistance and autonomous learning, between expedient solutions and transformative intellectual growth [13].

2.3. The "Learner-Absent" Problem: Toward Phenomenological Reorientation

This "learner-absent" tendency illuminates what AI accomplishes for language learners while obscuring what it phenomenologically means to exist as an AI-augmented learner. Phenomenology's imperative to "return to the things themselves" addresses this epistemic void [14]. Phenomenological philosophy posits that essential structures of phenomena resist disclosure through abstract reasoning or deductive logic alone; instead, researchers must suspend presuppositions, immerse themselves in first-person experiential accounts, and intuit invariant characteristics through eidetic reduction [15]. From this vantage point, AI transcends the status of neutral instrumental object awaiting utilization; it constitutes an existential presence reconfiguring learners' lifeworld. As one ChatGPT user articulated: "It simultaneously grants me a sensation of intelligence yet evokes uncertainty—is this authentically myself?" This utterance transcends instrumental appraisal, articulating fundamental questions of capability ownership and authorial authenticity [16]. Consequently, researchers must bracket theoretical preconceptions, attend sensitively to lived experience narratives, and extract underlying structural essences through phenomenological reduction and eidetic intuition [17].

2.4. Methodological Deficit: Experience Blindness in AI-Enhanced Language Education Research

Despite phenomenology's methodological promise, empirical applications to AI-mediated language learning contexts remain nonexistent, particularly investigations foregrounding negative experiential valences such as risk perception. Contemporary AI-supported language education research manifests dual problematic orientations: "functionalism" and "experience blindness." Abundant studies quantify learning outcome improvements, predict sustained usage intentions, and optimize pedagogical architectures, yet systematically neglect learners' interior phenomenological landscapes—affective fluctuations, interpretive labor, and meaning construction trajectories [18]. Even when learner emotions (anxiety, fatigue, enthusiasm) receive attention, inquiry remains trapped within variable operationalization and correlational analysis, failing to penetrate deeper existential questions: Why do students experience these particular affects? What ontological significance do these experiences carry? How do such feelings dialectically shape subsequent learning behaviors [19]? Addressing these theoretical-methodological deficiencies, our phenomenological investigation explores university students' lifeworld experiences in AI-mediated language learning, specifically examining risk perception's multidimensional structure: control anxiety beneath convenience seduction, epistemic burden triggered by accuracy uncertainty, metacognitive doubt ("Am I genuinely learning?") induced by cognitive offloading, and moral tension surrounding academic integrity transgressions [20].

3. Research Methodology

3.1. Research Paradigm and Epistemological Stance

The study takes its theoretical basis from interpretivist epistemology: reality does not exist as something objective and independent; on the contrary, individuals build up a meaningful world through constant interaction and introspection under certain social-cultural backgrounds. Different from the positivistic search for "neutral values" and "objectively measure," we admit the location-embedding nature and intersubjectivity of knowledge generation [21,22]. The sense of danger toward AI held by students is not some kind of "objective truth" waiting to be discovered, but rather the experience structure felt in the body, emotion, morality, and reflection when writing academically in practice with AI. Therefore, phenomenology method has become the inevitable choice of this study because it takes the "life world" (Lebenswelt) as its starting point, requiring us as researchers to put aside our judgment on whether AI is good or bad and to try to go into the perspective of learners to see how they give meaning to new technologies, how they struggle with identity under conflicting feelings, and how they accept or refuse AI in learning behavior. This study's theoretical framework integrates three core phenomenological concepts to elucidate the essential structure of AI risk experience. First, based on Merleau-Ponty's theory of "technological embodiment," we regard AI tools as a "body schema" that extends learners' cognitive capabilities; risk perception is awakened when technology transforms from a "transparent extension" to an "opaque obstruction." Second, employing Heidegger's distinction between "ready-to-hand/present-at-hand," we analyze students' ontological transition from "unconscious AI use" to "reflective examination of AI." Third, drawing on Ricoeur's theory of "narrative identity," we explore how AI intervention severs the ontological connection between "text-self," triggering authorship identity anxiety. At the metacognitive level, combining Flavell's metacognitive monitoring model, we understand students' questioning of "Am I still learning?" as an alertness to the loss of cognitive process visibility. In the agency dimension, borrowing from Bandura's self-efficacy theory, we explicate how the "empowerment-dependency paradox" undermines learners' sense of subjective control. This integrated framework provides multi-layered theoretical lenses for data analysis. As a researcher myself, I need to have the awareness that I belong to both sides—the side as a researcher in the field of educational technology, believing in the possibilities brought by AI; and the side as a fighter fighting against all kinds of oppression, guarding the learner's right to education. Such positioning provides me with both the conditions and limitations for understanding [23], so throughout the whole process of research, I adopted a member-checking strategy to improve the credibility of the research, asked participants to confirm the correctness and appropriateness of the analysis results of the interview data, and conducted peer-debriefing, exchanging emerging topics with experts in qualitative research.

3.2. Research Context and Participant Selection

The study was conducted in an academic English writing class at a comprehensive university in mainland China. This is a course offered from the second year to the third year. According to the regulations of this class, students could choose to use AI tools, but they had to mark it if they did so on their homework. Such "conditioned" permission gave us a good opportunity to explore college students' realistic behaviors instead of fully banning them from using AIs secretly or permitting them to freely use AIs without thinking about ethical issues [24]. Purposive sampling was adopted to identify suitable interviewees. After the end of teaching, the researcher sent out invitation emails to a total of 72 students who studied in the above two classes. Finally, we recruited 18 students, with maximum differences in how often they used AI tools (from "only consulted once/twice" to "relied heavily"), level of English proficiency (TOEFL iBT score from 90 to 108; IELTS band scores from 6.5 to 7.5), and discipline backgrounds (including science and technology, economics and management, liberal arts, and social science). All 18 participants were Chinese students whose native language is Mandarin, learning English as a foreign language (EFL), with an age range of 19–22 years (mean age 20.4 years, standard deviation 0.9), including 10 females (55.6%) and 8 males (44.4%). English proficiency was stratified according to standardized test scores: 4 participants (22.2%) were at lower-intermediate level (CET-4 ≤ 500 or IELTS 6.0–6.5), 8 participants (44.4%) were at intermediate level (CET-4/6 501–549 or IELTS 7.0 or TOEFL 90–99), and 6 participants (33.3%) were at upper-intermediate level (CET-6 ≥ 550 or IELTS 7.5+ or TOEFL 100+). Academic backgrounds spanned four fields to capture diverse academic writing needs: science and engineering 5 (27.8%), economics and management 4 (22.2%), humanities 5 (27.8%), and social sciences 4 (22.2%). Formal English learning experience ranged from 10–14 years (mean 12.1 years), ensuring all participants possessed foundational EFL competence while exhibiting different proficiency development trajectories. This diversity in demographic and linguistic characteristics provided a rich foundation of contextual variation for phenomenological analysis. Diversity rather than statistical representation was considered when choosing participants because we aimed to collect various experiences and views [25]. The epistemological foundation of phenomenological research determines the necessity of maximum variation sampling. According to Husserl's theory of eidetic intuition, the essential structure of phenomena must be revealed through "imaginative variation"—that is, seeking common invariant structures across experiences in different contexts and subjects. Therefore, we deliberately selected participants with significant differences in AI usage frequency, English proficiency, and academic backgrounds, aiming to highlight the essential characteristics of risk perception by contrasting "extreme cases": Which experiential elements persist across all contexts? Which vary by context? For example, when both low-frequency and high-frequency users report "capability erosion anxiety," this cross-contextual resonance points to an essential dimension of risk experience. Maximum variation sampling is not for statistical representativeness, but rather to perceive universality through diversity, enabling phenomenological reduction to reach the level of "eidetic insight." To ensure their privacy, all participants chose to use aliases during interviews. Before being interviewed, the participants were asked to sign the informed consent form and were told they could stop the interview at any time without affecting their final grade. However, there might still be "response bias," because teachers and students have hierarchical relations, and it may not be easy for students to speak out frankly. In other words, participants might show themselves as "responsible users" but hide their true struggles [26].

3.3. Data Collection Methods

Data Collection: In-depth phenomenological interviews were conducted, together with experience journals, to collect data on both "in-the-moment" and "afterward" aspects of how students experienced using AI. The participants had one to two semi-structured interviews, lasting from 60 min to 90 min. Instead of being information extraction Q&A sessions, interviews took the form of dialogical investigations following established phenomenological research principles [26,27]. The design of the interview protocol underwent a three-round iterative optimization process. First, based on Van Manen's phenomenological interview principles and Heidegger's theoretical framework of "Being-in-the-world," the research team initially developed an open-ended question framework covering four dimensions: temporality experience, bodily perception, affective tension, and meaning construction. Second, two qualitative research experts and one applied linguistics professor were invited for expert consultation, and based on their feedback, the phenomenological purity of the questions was adjusted—questions presupposing causal relationships (such as "Does AI cause your ability to decline?") were deleted, and guidance for experience retrospection was enhanced (such as "Please take me back to that specific moment of using AI"). Third, two pilot interviews were conducted before formal interviews, which revealed participants' difficulty understanding abstract concepts (such as "risk perception"), so questions were concretized into life-scenario narratives ("Could you describe an AI usage experience that made you feel uneasy?"). Pilot data were not included in the final analysis but provided an important basis for question optimization. This iterative process ensured that interview questions remained faithful to phenomenological methodology while being close to participants' lifeworld expression habits. Researchers issued open invitations, such as "Can you tell me about one time using ChatGPT which impressed you most?" Phenomenological questioning was also asked: "What do you feel physically in this moment? What is going on internally for you?". Such probes invited participants back to particular moments and transformed fuzzy feelings into words. Not to over-intervene with preconceived conceptual categories, the interview guide offered only the topic to talk about rather than fixed questions. During the interview, researchers held an attitude of "active listening," allowing there to be silence and hesitation. Such nonverbal cues frequently unveil further difficulties in making sense. All the recordings were recorded in full and transcribed verbatim, with tones/pause/emotion included (e.g., laughing/sigh) so as to keep the feeling aspect of experience intact. Concurrently, the experience journal asked students to document at least five "critical instances" of using AI within three weeks.

3.4. Data Analysis: Interpretive Thematic Analysis

Data analysis adopted the spiral cycle logic of Interpretive Phenomenological Analysis (IPA), refusing to dissect the experience narrative into fixed code categories. Firstly, the data was read again and again; the researcher carefully read the transcript of each of the 18 interviews and the 87 experience diaries, word by word, recording preliminary feelings, doubts, theoretical connections, etc., in the blank space next to the text, in order to seize the "first contact" impressions of emotion tension, contradiction rhetoric, silence rupture in the experience story [28]. Secondly, in the process of "experiential coding," the purpose is not to "label" the text, but to rebuild the meaning world of the interviewee with interpretative language, such as "I feel I'm smarter but not really," which is preliminarily encoded as "illusory sense of improved ability." Then, through continuous comparative analysis, cluster analysis, and so on, we found the resonance among cases, summing up three core topics from them: the contradiction of efficient temptation and power erosion, labor transformation triggered by accurate anxiety, and reconstruction of self in the process of meta-cognition reflection. The topic name has been modified many times in order to be loyal enough to the language of the interviewees, while abstracting out the phenomenological core [29]. This study adopted a "qualitative-dominant, quantitative-supplementary" model (QUAL-quan) in a mixed-methods design, with quantitative data serving to enrich phenomenological description rather than hypothesis testing. Crucially, numerical patterns function not as causal explanations but as contextual scaffolding that renders experiential variations more visible—revealing which risk perceptions intensify across usage frequencies or proficiency levels, thereby directing phenomenological attention toward theoretically significant lived tensions rather than statistical relationships. Specific operations were as follows: First, in experience logs, participants were asked to self-report AI usage frequency (times per week) and duration per use, based on which usage intensity was categorized into three types—low-frequency use (≤1 time/week), medium-frequency use (2–4 times/week), and high-frequency use (≥5 times/week). Second, English proficiency was objectively stratified according to official standardized test scores: lower level (CET-4 ≤ 500), intermediate level (CET-4/6: 501–549), and higher level (CET-6 ≥ 550). Third, variables such as time-saving perception and anxiety intensity were measured through structured log scales (5-point Likert scale); 18 participants submitted a total of 87 logs, yielding 435 data points. Coding example: original text "I feel smarter, but it doesn't feel real" → initial note "illusory sense of capability enhancement + identity doubt" → experiential code "empowerment-dependency paradox" → final theme "agency erosion." Quantitative data were presented through descriptive statistics to show pattern distribution, forming triangulation with in-depth interview texts to jointly reveal structural characteristics of risk experience.

3.5. Researcher Reflexive Positioning

The qualitative research epistemology holds that "pure objectivity" does not exist but only exists as a fallacy. The researcher's theoretical background, values, and life experiences will always be part of the knowledge generation process. As a novice researcher in the field of educational technology, I developed two opposing attitudes towards using artificial intelligence in education: on one hand, I tend to be technologically optimistic (that is, believing it can promote the popularization of knowledge and provide individualized teaching); on the other hand, under the influence of critical pedagogy, I still have certain reservations regarding technology's usurpation of learners' power. Such "cognitive conflicts" also generated some internal contradictions when conducting the interview: if students reported feeling anxious about being replaced by AI, my empathetic response may trigger further exploration; if they felt empowered by AI, then maybe inadvertently show some doubt. In addition, as someone who uses artificial intelligence software every day for searching literature and proofreading papers, such "insider" feelings bring about a sense of identification with them; meanwhile, cause excessive projection—mistaking my inner struggle for their real emotions. Therefore, I continuously wrote reflective diaries throughout the entire research process: recorded feelings after each round of interviews, revised previous assumptions, and was confused about theory [30,31].

3.6. Ethical Declaration

This study strictly adheres to the following ethical principles: The study was conducted in accordance with the Declaration of Helsinki, and approved by the Institutional Review Board (or Ethics Committee) of the Faculty of Education, The National University of Malaysia (protocol code UKM PPI/111/8/JEP-2024-927 and date of approval 15 November 2024). All research procedures involving human participants were reviewed and approved prior to data collection, ensuring compliance with international ethical standards for educational research. The approval covered all aspects of participant recruitment, informed consent procedures, data collection methods (semi-structured interviews and experience journals), data storage and confidentiality measures, and participant rights protection mechanisms. Regarding informed consent, all 18 participants signed written informed consent forms, clearly stating the research purpose, data usage methods, the right to voluntary participation, and the right to withdraw at any time, with particular emphasis that participation or withdrawal would not affect their course grades. Regarding anonymization and confidentiality, all interview records and questionnaire data have been completely anonymized; names mentioned in the text (such as "Xiao Li" and "Xiao Wang"), institutional names, and specific locations all use pseudonyms or codes; original data (including recordings and interview transcripts) will be destroyed within 3 years after publication to ensure long-term confidentiality. Regarding the minimal risk principle, the study's intervention with participants was limited to completing a 60–90-minute interview and three weeks of experience log recording, involving no physiological or psychological risks. Regarding data destruction commitment, we promise that data will be properly handled after completing the research, with electronic files encrypted for storage and permanently deleted after the specified period. All research procedures prioritize the protection of participants' rights and interests, ensuring dual compliance with academic integrity and ethical standards.

4. Results Analysis

4.1. "The Panic of Excessive Convenience": Efficiency Temptation and Agency Erosion

4.1.1. Accelerated Writing: Time Savings versus Learning Shortcuts

Students all described a "time compression" paradox—the tool could shorten a several-hour writing task to ten minutes, but meanwhile brought new worries: what exactly are these skipped "struggle moments"? Xiao Li (pseudonym), the student quoted above, frankly said in the interview: "ChatGPT provides me with a complete reasoning result within three seconds. It may take me half an hour to write down this argument. At first I feel like I have won, but later I find out that the thinking, trial and error, and self-dialogue that should have taken place in these thirty minutes have all been erased." This feeling exposes a profound contradiction between efficiency and learning—when technology removes "desirable difficulty," the learning process itself is "instrumentalized" and becomes an obstacle to be skipped [32]. **Table 1** shows the correspondence between time saved and learning losses reported by eighteen participants. Interestingly, high-frequency users (5+ times per week) saved an average of 74% of writing time [33]. **Figure 1** shows a U-shaped relationship between users' frequency of using AI tools and their feelings towards time saved vs. learning loss. Anxiety decreases before increasing again as frequency increases. Moderate users seem to have found some kind of "balance point," while those who rely heavily on them fall into the "efficiency trap" and become very anxious.

Table 1. Participants' frequency of using AIs, time saved, and perception of learning loss.

Usage Frequency Group	Number of Participants	Average Time Savings Ratio	Percentage Reporting "Skipping Thinking" Concerns	Percentage Reporting "Capability Degradation" Anxiety
Low (≤1 time/week)	4	45%	25%	0%
Moderate (2–4 times/week)	8	62%	50%	38%
High (≥5 times/week)	6	74%	83%	67%

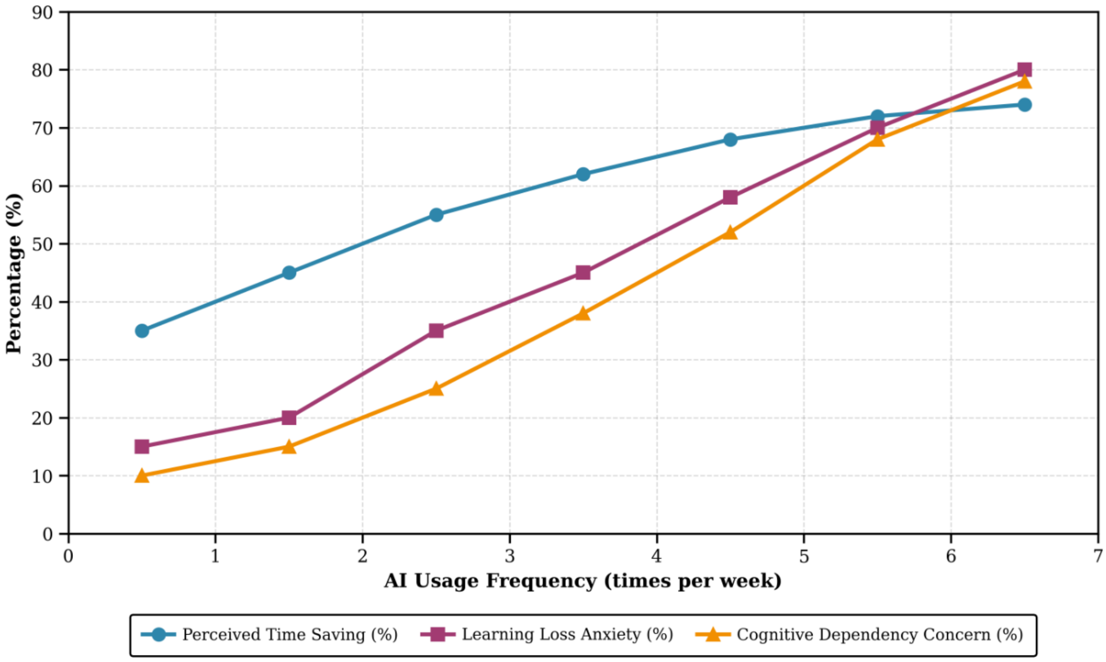

Figure 1. Relationship between AI Usage Frequency, Time Savings Perception, and Learning Anxiety.

4.1.2. The Capability-Dependency Paradox: Empowerment or Deskilling?

Participant narrative revealed a core paradox: AI was felt to be both enhancing and eroding capability at the same time. In his experience journal, Xiao Wang wrote, "Like wearing glasses, once you put them on, you can't take them off again." "Now I need to ask ChatGPT before writing English compositions, or I feel I won't write well." The psychological crutches metaphor appeared repeatedly in interview data. Pointing to the subtle shift of power relations: From the perspective of students, AI is a complement to make up for language deficiencies. However, as the number of uses increases, the tool changes from "optional" to "indispensable". From "complement" to "replacement" [34]. Xiao Zhang's language was more direct: "I'm beginning to fear that if there's no AI, can I still write a good sentence? Am I really learning or just faking it as someone who knows how to write?" Such concerns do not relate only to the realistic risk of skill decline, but also touch upon the fundamental questioning of oneself. When my" capacities are outsourced to technology, does this mean the integrity of me as a learner has been damaged? According to **Table 2**, the feelings of being empowered by AI were stronger among lower-level English learners (with CET4 scores ≤ 500).

Table 2. Differential Experiences of AI Dependency Among Students with Varying English Proficiency Levels.

English Proficiency Group	Number of Participants	Percentage Reporting "Empowerment Feelings"	Percentage Reporting "Threat Feelings"	Percentage Reporting "Capability Degradation Anxiety"	Percentage Adopting "Conscious Non-Use" Strategies
Low Level (CET-4 ≤ 500)	4	75%	25%	25%	50%
Medium Level (CET-4/6: 501–549)	8	50%	38%	50%	63%
High Level (CET-6 ≥ 550)	6	17%	62%	83%	83%

4.1.3. Whose Text Is It Anyway?: The Case of Authorial Identity.

According to the narrative identity theory proposed by Ricoeur, text is the extension of oneself; writing is how internal thought becomes visible through external symbols [35,36]. The intervention of artificial intelligence breaks this connection, and when the sentence is produced directly by the machine, the "umbilical cord" between the author and the text is broken. The students cannot find out whether it is their own voice. According to **Table 3**, compared with different levels of artificial intelligence usage, there are also changes in students' identity cognition. Under the condition of slight modification (Grammar Correction Only), 89% of students still believe that "it is my work." If the whole paragraph is replaced by artificial intelligence, the proportion drops sharply to 22%. Instead, they have identified themselves as co-authors (44%) or just editors (34%). More conflicts arise among different cultures and disciplines. Students who are from a collectivistic cultural background (Xiao Sun) hold a more inclusive view: "The idea of others has always been absorbed during the process of writing. Why not treat artificial intelligence as one kind of 'others'?" But humanities and social sciences majors are more concerned about originality, the fundamental attribute of academic identity [37].

Table 3. The Recognition of Students' Authorial Identity under Different Levels of AI Usage.

Degree of AI Use	Number of Participants	Consider "Entirely My Work"	Consider "Co-Created with AI"	Consider "I'm Just AI's Editor"	Feel "Identity Anxiety/Unease"
Light Modification (grammar/spelling correction)	9	89%	11%	0%	22%
Moderate Use (sentence rewriting/expansion)	6	50%	33%	17%	50%
Heavy Dependence (paragraph/full text generation)	3	22%	44%	34%	89%

4.2. "Hallucinations" and "Gatekeepers": Accuracy, Anxiety, and Verification Burden

4.2.1. When AI "Talks Nonsense with Confidence": The Collapse of Accuracy Trust

The student's trust in artificial intelligence has experienced a painful shift from blind trust to suspicion, usually triggered by one "betrayal event." Xiao Zhao said in the interview: "I found out that the article cited by it does not exist at all: the author's name, journal's name, and the publication year are all fake. At that moment, I was shocked and felt cheated." Such hallucinations are far beyond finding some technical flaws; rather, they fundamentally question whether artificial intelligence can be relied upon. If artificial intelligence can confidently make up facts like this, can we rely on what it produces anymore? As for how to cope after being betrayed, as shown by Xiao Sun: "Currently, I no longer dare to use it directly but need to verify each sentence. It's even more tiring than writing myself." In other words, there is a paradoxical reversal from "cognitive offloading" to "cognitive overload." AI should relieve our cognitive burden, but instead, the uncertainty of the accuracy of AI makes us always vigilant [38] (**Table 4**).

Table 4. Types, Frequencies, and Identification Rates of AI Errors Encountered by Students.

AI Error Type	Encounter Frequency (% of Total Sample)	Average Identification Rate	Engineering Student Identification Rate	Humanities/Social Science Student Identification Rate	Trust Damage Severity (1–5 Scale)
False Citations (fabricated literature)	58%	67%	83%	50%	4.6
Factual Errors (historical/data errors)	39%	72%	89%	56%	4.2
Logical Contradictions (inconsistency)	22%	56%	67%	44%	3.8
Outdated Information (old training data)	33%	44%	50%	38%	3.3

4.2.2. From Creator to Verifier: The Transformation of Labor Nature

Table 5's revelation of labor time reallocation is not merely a presentation of quantitative data, but reflects an ontological crisis in learner identity. Before AI intervention, 78% of time was devoted to conception and writing—this is the core practice of learners as "knowledge creators," externalizing internal thinking into visible text through linguistic encoding, completing what Ricoeur describes as the construction of "self-text" identity [39]. However, after AI use, this proportion plummeted to 35% (prompt engineering 23% + initial generation 12%), replaced by 65% of validation labor time (fact-checking 35% + rewriting 12% + polishing 10% + other 8%). This transformation signifies learners' regression from "meaning-makers" to "gatekeepers," with their cognitive role shifting from active generation to passive examination. A deeper paradox lies in the fact that the linguistic sensitivity, critical thinking, and literature retrieval capabilities required to validate AI output are precisely the shortcomings students initially hoped to compensate for through AI. As shown in **Figure 2**, lower-ability students exhibit a 47% "pretend acceptance" rate due to a lack of validation capability, while higher-ability students, though capable of effective validation (72% time proportion), consequently question AI's efficiency value. More critically, verification labor itself required capabilities that students originally hoped AI would compensate for. Judging whether academic expressions were appropriate required language sensitivity. Identifying logical gaps demanded critical thinking. Verifying citation authenticity needed literature retrieval skills [40]. This formed a paradoxical cycle. Those with insufficient capability depended more on AI. But they also lacked verification abilities. Thus, they fell into the cognitive blind spot of "not knowing what they don't know" [41]. **Figure 2** visualizes labor time reallocation after AI use among students with different capability levels. Low-capability students showed high rates of "pretend acceptance" (directly adopting unverified content) at 47% due to insufficient verification abilities. High-capability students could effectively verify (verification time occupied 72%). However, they also questioned the efficiency value of AI use because of this burden.

Table 5. Changes in Student Writing Time Allocation before and after AI Use.

Writing Stage	Average Time Proportion before AI	Average Time Proportion after AI	Magnitude of Change
Conception and Outlining	25%	12%	−52%
Drafting Initial Text	53%	23%	−57%
Prompt Engineering and AI Interaction	0%	18%	+100%
Verification (facts/citations/logic)	8%	35%	+338%
Revising and Rewriting AI Content	0%	12%	+100%
Language Polishing and Format Adjustment	14%	10%	−29%

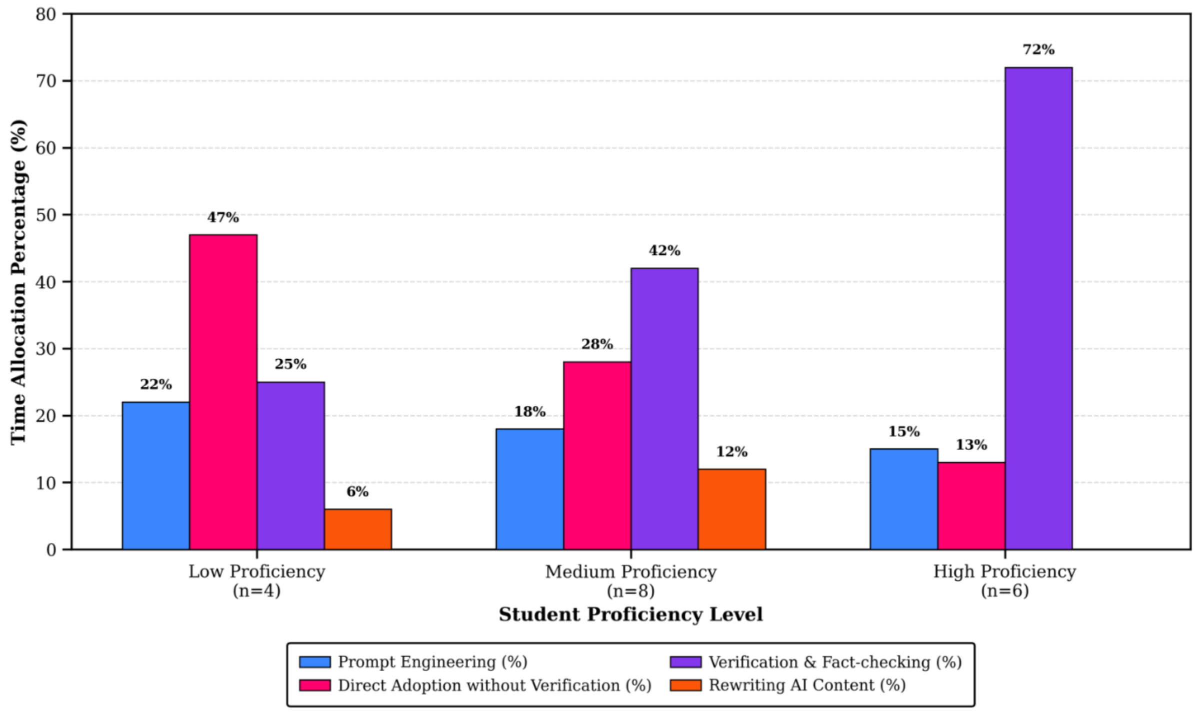

Figure 2. Labor Time Reallocation After AI Use among Students with Different Capability Levels.

4.2.3. Embodied Experience of Academic Risk: Grades, Reputation, Academic Integrity

Students worried not only cognitively about AI errors. They also experienced imagined torments of punishment, questioning, and labeling at bodily and emotional levels. Xiao Zheng wrote in his experiential journal: "What if the teacher detects it with plagiarism software? I'm done for. In those days, after submitting, my heart races and palms sweat whenever I see an email notification from the teacher." This "post-submission anxiety" was a delayed, continuous emotional burden. It transformed academic writing from knowledge demonstration into waiting for moral judgment. More specific fears came from peer surveillance. Xiao Qian described: "Students in the group chat discuss who got caught. This makes me very nervous. Although I only use AI to fix grammar, I don't even dare mention that now." This spreading fear revealed something Foucault discussed about disciplinary power. Through the "panopticon" mechanism, power becomes internalized. Students need not actually be monitored. The imagination of surveillance possibility alone produces self-censorship. **Table 6** presents three types of academic risks reported by students and their coping strategies. Seventy-eight percent worried about "grade invalidation" (low scores or redoing work due to AI errors). This represented the most direct utilitarian fear. Sixty-one percent worried about "academic reputation damage" (being questioned about integrity by teachers or peers). This involved the protection of the social self. Forty-four percent experienced deeper "moral self-blame" (feeling guilty even if undetected). Notably, institutional ambiguity significantly amplified these anxieties. When school policies vaguely stipulated "reasonable AI use" without defining boundaries, students fell into continuous uncertainty about "how much we actually use" [42,43]. Xiao Xu's confusion was highly representative: "The teacher said we could use it, but must note it.

Table 6. Types of Academic Risks Reported by Students, Concern Levels, and Coping Strategies.

Academic Risk Type	Reporting Percentage	Average Anxiety Intensity (1–5 Scale)	Main Coping Strategy	Percentage Adopting This Strategy
Grade Invalidation (low scores/redo due to AI errors)	78%	4.3	Excessively verify every detail	68%
Academic Reputation Damage (questioned about integrity)	61%	4.6	Reduce AI usage frequency	44%
Flagged by Detection Tools as AI-generated	56%	4.1	Manually rewrite AI sentences	52%
Moral Self-blame (internal guilt)	44%	3.8	Use AI only in low-risk assignments	39%
Peer Reporting or Competitive Disadvantage	33%	3.5	Keep AI use confidential	67%

4.3. "Am I Still Learning?": Metacognitive Anxiety and the Threat to Deep Learning

4.3.1. Outsourcing Thinking: Loss of Cognitive Process Visibility

Table 7 presents changes in students' metacognitive awareness. Before using AI, 83% of students could clearly describe their thinking paths ("This is how I thought"). After using AI, this proportion dropped to 28%. Correspondingly, the proportion reporting "uncertain idea origins" surged from 11% to 61% [44]. More worryingly, 39% of students expressed self-perception of "thinking ability degradation." This was not merely an objective capability decline. Rather, it represented a shaking of subjective identity—the sense of "me" as a thinker became diluted. **Figure 3** visualizes this process through the cognitive load theory framework. In traditional writing, students' working memory must simultaneously process content generation, language encoding, and structure organization. Cognitive load is high but promotes deep processing. After AI intervention, students' cognitive load shifts from "generative" to "evaluative." This appears to reduce the burden. Actually, it deprives those "desirable difficulties" that promote long-term learning. Xiao Jia's reflection possessed keen insight: "Thinking about it now, the pain of not being able to write before was actually learning something. AI lets me skip the 'not knowing what to say' stage. But that might be exactly where learning happens." This belated awakening suggests something important. Comfort and growth are often opposed. Technology precisely tempts students to choose the former and abandon the latter.

Table 7. Changes in Student Metacognitive Awareness Before and After AI Use.

Metacognitive Indicator	Before AI Use	After AI Use	Magnitude of Change
Can clearly describe own thinking path	83%	28%	−66%
Can trace idea generation process	72%	33%	−54%
Uncertain about idea origins (mine vs. AI's)	11%	61%	+455%
Feel "thinking was skipped"	6%	56%	+833%
Self-assess "thinking ability degradation"	0%	39%	N/A
Can monitor own learning progress	67%	22%	−67%

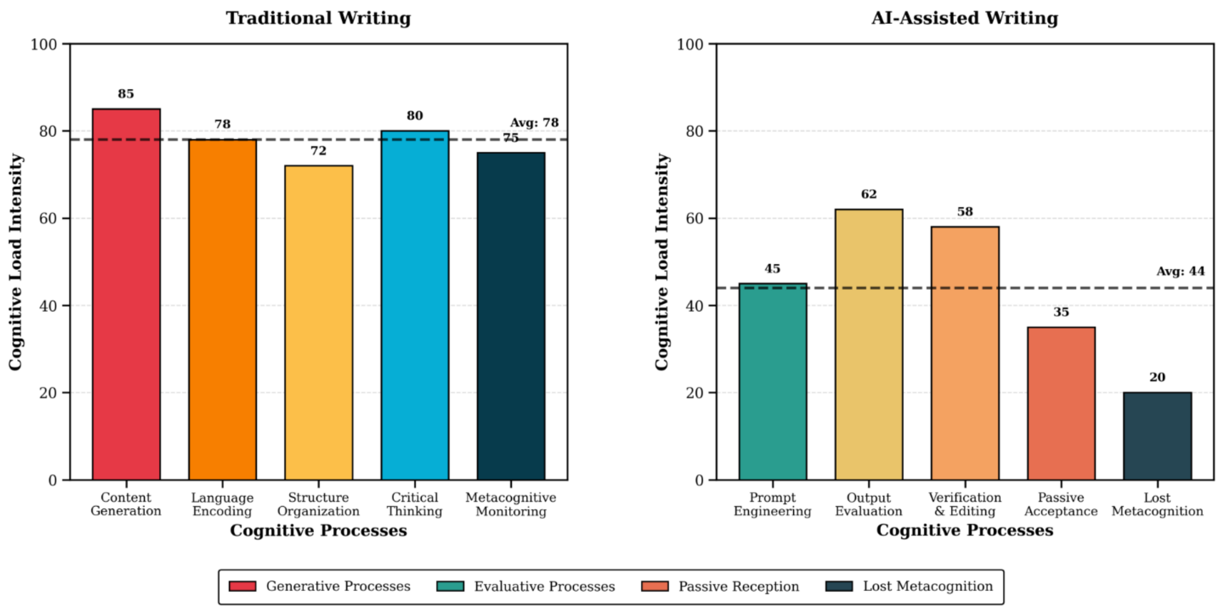

Figure 3. Cognitive Process Load Comparison between Traditional Writing and AI-Assisted Writing.

4.3.2. The Meaning of "Struggle": The Disappearance of Desirable Difficulties

After reflecting retrospectively, students began to realize that those hard times previously considered "learning obstacles" are actually the most "alive" period of cognitive growth. As another interviewee, Xiao Xu, said: "Thinking about it now, not knowing how to write is actually 'something I have learned.' Stuck here and don't know how to say it; I will look up the dictionary, find example sentences, try many times... that's 'learning.' " This reflects the essence of Vygotskian ZPD theory: learning does not occur in comfort zones, but rather in "struggling areas." As expressed by Xiao Jia, "When AI solves problems for you directly from 'not knowing how to speak,' the 'not knowing' time that makes your brain generate new circuits seems missing." In fact, according to the psychological concept of eustress, moderate levels of cognitive challenge promote deep processing and long-term memory formation. Instead, too much ease hinders learning transfer [45]. **Table 8** shows how students changed their views on whether "struggling" is valuable. Before trying out AI, only 22% felt that it was useful to encounter difficulties when writing. By contrast, 61% took them as "problems that need to be solved." Afterwards, however, 72% started considering again why we need to suffer. Because "maybe we really need to struggle." Such changes originated from cherishing what has been lost. If everything becomes smooth later on, students will even miss this feeling of "hard work but rewarding." Even more subtle differences are found in situations. It still prefers efficiency with AI in routine homework rather than without AI (78%). However, under special conditions—like final examinations or job application letters—56% choose not to use AI so that they can "keep their true abilities." As described by Xiao Yao: "No AI allowed during the final exam, then I found myself unlearned here because my previous homework got a high score, which made me feel safe [46], but it turned out to be just an illusion. This experience made some students take a 'consciously struggle' strategy: use AI in low-risk tasks, save time; do not use AI in high-stakes situations, maintain basic skills."

Table 8. Transformation in Students' Perception of "Writing Struggle" Value.

Attitude toward "Struggle"	Before AI Use	After AI Use (Reflection Period)	Contextual Difference: Daily Assignments	Contextual Difference: Important Tasks
Believe "difficulties have learning value"	22%	72%	17%	61%
View as "obstacles to be eliminated"	61%	17%	78%	28%
Ambiguous/contradictory attitude	17%	11%	5%	11%
Adopt "conscious struggle" strategy	0%	44%	Use AI for low-risk	Avoid AI for high-risk
Miss "effortful but rewarding" feeling	6%	67%	-	-

5. Discussion

5.1. Beyond Binary Opposition: Risk as Experience Rather than Attribute

In conclusion, the key discovery of this study has challenged the existing theoretical research paradigm on technology risks: Risks neither objectively belong to AI tools nor are they probabilistically measurable. Instead, they are "meaningful worlds" constructed by learners through body sensation-emotion-reflection under certain situational conditions [45]. This finding fundamentally contests the Technology Acceptance Model's (TAM) foundational assumption that adoption decisions emerge from rational cost-benefit calculations of perceived usefulness and ease of use. TAM presupposes a stable, pre-existing "risk object" awaiting evaluation; our phenomenological evidence reveals risk as dynamically constituted through lived experience—the same AI feature (rapid response generation) manifests as empowerment for one learner yet threatens another, contingent upon situational context, proficiency levels, and identity negotiations. We thus propose replacing TAM's input-output logic with a hermeneutic framework: learners do not "perceive" pre-given risks but actively interpret technological encounters within their lifeworld horizons. This change also brings new epistemological insights. We no longer take for granted that "AI has risks," but ask instead, "How do students feel risky?" and "What does risk mean to them?" [46]. What we found is that even if it is the same technical characteristics (how fast the AI tool generates responses), different students will have different feelings under different assignment scenarios. It may be exciting to empower me ("Finally I can speak up during academic discussion"). Or it may feel like threats to overwhelm me ("It's taking away my advantage"). These diverse and changing feelings cannot be reduced to the score level or the causal relationship of acceptance models. In particular, the feeling of risk itself is "contradictory." Students do not simply accept/reject technologies, but constantly adjust boundaries between efficiency vs deep learning, convenience vs authenticity, dependence vs independence [47]: "Maybe this is not about accepting/not accepting AI. Instead, it's about how you don't get lost while using AI," as Xiao Ma put it. This reminds us that education research needs to change its focus from identifying/risk avoidance to understanding/conversing about the sense of risk. We need to recognize that, rather than problems waiting to be solved, the contradictions involved when adopting new technologies are situations we all need to share.

5.2. Educational Implications of Contradictory Experiences

The contradictory experience of students using AI needs to be taken seriously instead of being ignored: on the one hand, they want to be efficient but fear dependence; on the other hand, they are grateful for empowerment but doubt whether it is really their own. Such contradictory feelings are not "cognitive confusion" or "developmental immaturity," but rather show "true educational insight." In fact, any real learning cannot avoid tension and uneasiness [48]. These contradictions naturally present teaching moments for fostering reflection ability. Once students say, "I know AI will save me time, but at the same time I feel like I'm losing something," this is the moment of metacognition, which is "reflection on reflections." This reflective awareness itself belongs to the key competence of 21st-century talents [49]. From a sense-of-control perspective, it is precisely because of contradictory experiences that students shift from being a tool user to becoming an active creator of meanings. They begin to develop control behaviors such as "consciously not using AI tools," flexibly choosing strategies based on situations, and setting boundaries for themselves, which are new ways of taking charge under technology conditions. Instead of avoiding, educators need to bring these contradictions out into the open and discuss with them the difficulties encountered during the use of AI in class. Or write reflective diaries to describe the journey of thinking, analyze cases, weigh the advantages and disadvantages of different ways of using AI, etc., so as to help students turn vague anxiety into clear self-perception [50]. The key point is to change the binary opposition of current educational discourses. Do not simply educate students that AI is good or bad. Instead, we should grow judgment together with them in ambiguous situations. Help them build subjecthood in contradiction. Perhaps this is the mission of education in the era of artificial intelligence. Operationalizing these phenomenological insights, our pedagogical strategies directly address the three experiential structures uncovered: meta-reflective tasks combat cognitive offloading invisibility (the "Am I still learning?" anxiety); critical AI literacy modules target the verification burden paradox (transforming "gatekeepers" into informed critics); dual-track assessment honors both the efficiency-agency dialectic and authorship identity struggles. This theory-practice alignment ensures interventions do not impose external solutions but rather amplify learners' existing hermeneutic labor—making visible what they already intuitively sense yet struggle to articulate. Based on research findings, we propose three types of actionable pedagogical strategies. First, design "meta-reflective tasks" to promote cognitive offloading awareness: require students to submit "dual-track writing journals," with the left column recording AI-generated content and the right column reconstructing "how I would think without AI," visualizing skipped cognitive processes through comparison; implement "thought process retrospection" assignments, having students reconstruct complete reasoning chains of problem-solving with mind maps, marking AI intervention points. Construct a "critical AI literacy" curriculum module encompassing four dimensions: technical cognition (understanding LLM working principles and limitations), ethical judgment (case analysis of academic integrity dilemmas), verification capability (training fact-checking and logical critical thinking skills), and boundary setting (formulating personalized AI usage contracts). Third, adjust assessment policies to balance accountability and stress reduction: adopt "process portfolio" assessment, requiring students to submit complete trajectories of initial draft—AI interaction records—revised draft; establish dual tracks of "AI-free assessment" and "AI collaboration tasks" running in parallel, with the former ensuring basic competency evaluation and the latter recognizing tool collaboration capability; establish an "AI usage transparency" declaration mechanism, incorporating the labeling behavior itself into integrity scoring, transforming punishment into educational dialogue.

6. Conclusion

By using the method of educational phenomenology, we explore university students' deep feelings about the risk perception of artificial intelligence for language learning. A world of meaning behind the use of technology is revealed.

(1) The research has built up an epistemology of risk as "experienced construction" instead of "objective attribute", which is against the variable-based thinking mode of the traditional technology acceptance model (TAM).

(2) There are three dialectical contradictions derived from the above data. The first contradiction is the tension between "efficiency temptation" and "agency erosion." The second one is centered around the "labor transformation" provoked by "accuracy anxiety," and the last one deals with how "metacognitive questions" prompt "self-reconstruction." As such, all these three aspects together form the "existential condition" of students to dance with AI.

(3) "Learners do not pick things up passively but come up with their own ways to take control (e.g., 'consciously not using something') in dealing with contradictions." This is another novel way that learners exercise their power in this new tech era.

(4) Instead of treating them as problems to be solved through punishment and discipline, we need to make these contradictory experiences visible as the conditions that can promote critical reflection on what is going wrong. Rather than punishing students who violate school norms, we should support them in developing their own judgments about how to act with others in situations where there are no clear rules; dialogue, not discipline, will be key.

(5) The present study provides a methodological demonstration of how to conduct qualitative inquiry in education. Taking a research approach that is based on learners' voices, grounded on the experience of narration, and oriented toward the interpretation of meaning, we found something "beyond instrumentality". That is, it would be valuable if future studies could follow up on the development over time of students' attitudes towards AI, as well as investigate differences in the expression of perceived risk under different cultures.

Author Contributions

Z.G.: Conceptualization, data curation, formal analysis, methodology, and writing—original draft; R.S.A.R.A.R.: Supervision, validation, and writing—review & editing; N.A.: Supervision, validation, and writing—review & editing. All authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Review Board (or Ethics Committee) of the Faculty of Education, The National University of Malaysia (protocol code UKM PPI/111/8/JEP-2024-927 and date of approval 15 November 2024). All research procedures involving human participants were reviewed and approved prior to data collection, ensuring compliance with international ethical standards for educational research. The approval covered all aspects of participant recruitment, informed consent procedures, data collection methods (semi-structured interviews and experience journals), data storage and confidentiality measures, and participant rights protection mechanisms.

Informed Consent Statement

Regarding informed consent, all 18 participants signed written informed consent forms, clearly stating the research purpose, data usage methods, the right to voluntary participation, and the right to withdraw at any time, with particular emphasis that participation or withdrawal would not affect their course grades.

Data Availability Statement

The data used in this study are available from the corresponding author upon reasonable request.

Acknowledgments

We are grateful to the National University of Malaysia (UKM) for its academic support.

Conflicts of Interest

The authors declare no conflict of interest.

References

1. Saadati, M.; Talebi, H.S. Cross-Linguistic Awareness as a predictor of language learning motivation: A bayesian perspective. *Discover Educ.* **2025**, *4*, 469.
2. Pham, T.A.; Abdullah, M.R.T.L. Validating and prioritizing key indicators for blended MOOC implementation in English language learning using the fuzzy Delphi method. *MethodsX* **2025**, *15*, 103668.
3. Lu, X.; Yang, Q.; Wei, J.; et al. From belief to evidence: Simpler immediate feedback improves language learning and confidence in semi-open-ended questions. *Front. Educ.* **2025**, *10*, 1654809.
4. Nakamura, J. Language learning and socioemotional well-being in early educational migration: Japanese children's transition into English-medium education in Malaysia. *J. Multiling. Multicult. Dev.* **2025**, *46*, 3833–3851.
5. Seruji, Z.; Salleh, M.M.; Dani, N.A. The effect of bilingual practices on foreign language learning experiences of international students in higher education. *J. Lang. Teach. Res.* **2025**, *16*, 1899–1909.
6. Kapxhiu, L. AI in language learning assessment: Examining the limitations of online testing and the reliability of teacher judgement. *Acad. J. Bus. Adm. Law Soc. Sci.* **2025**, *11*, 59–72.
7. Santos, J.C.d.; Hernández, A.M. Emotional Intelligence and Beliefs about English Language Learning: A Case Study with Pre-service Teachers. *Forum Linguist. Stud.* **2025**, *7*, 83–96.
8. Alsagoafi, A.A.; Jassim Aljamal, A.; Alahmad, M.A.; et al. A Bibliometric Analysis of AI-Powered Technologies in Language Learning: Trends from 2022 to 2025. *Forum Linguist. Stud.* **2025**, *7*, 1362–1379.
9. Amato, M.; Arias, G.I.M.; Slomp, N. Predicting language learning strategies from competence need satisfaction and autonomous motivation. *Discov. Psychol.* **2025**, *5*, 144.
10. Jiang, S.; Numtong, K.; Asavaratana, W. Toward sustained interaction: Investigating the drivers of continued use of AI chatbots for language learning in Confucius Institutes. *Front. Educ.* **2025**, *10*, 1656204.
11. Saleh, N.; Idawati; Akhir, M.; et al. Gamification in foreign language learning: A pathway to inter-cultural communication understanding in reading comprehension. *Theory Pract. Lang. Stud.* **2025**, *15*, 3669–3679.
12. Refat, N.; Dang, T.T.; Rahman, M.A.; et al. Implementing a Comprehensive Instructional Design Framework for Technology-Enhanced Language Learning to Enhance Engagement, Self-Confidence, and Reduce Cognitive Load: A Qualitative Study on Learning Experiences. *J. Lang. Teach. Res.* **2025**, *16*, 1791–1802.

13. Zhang, A.R.; Jiang, C.L. Research on college students' foreign language speaking anxiety based on large language models. *J. Liaoning Univ. Technol. (Soc. Sci. Ed.)* **2025**, *27*, 51–56. Available online: https://ir.bjut.edu.cn/irpui/item/445003 (in Chinese).
14. Jalambo, M.O.; Çakmak, F.; Akhter, S. Effects of self-regulated vocabulary learning with chatbots on incidental and collocational vocabulary learning and foreign language learning boredom. *Discov. Educ.* **2025**, *4*, 501.
15. Li, C.; Mutlu, K.A. The interplay of personal learning experience, social emotional learning and autonomy in promoting well-being in AI-assisted language learning: A self-determination theory approach. *Eur. J. Educ.* **2025**, *60*, e70354.
16. Dayanand, A.; Devi, U.; Jinu, K.T.; et al. Revitalising the Irula language through mobile language learning application. *Cureus J. Comput. Sci.* **2025**, *2*, es44389-025-08635-7.
17. Peura, L.; Mutta, M. Use of a robot in an imaginary space. Robot-assisted language learning with a friendship booklet (*carnet d'amitié*). *Educ. Linguist.* **2025**, *4*, 234–256.
18. Zheng, M.Y.; Li, S.Y.; Li, G. Research on the formation mechanism of teachers' educational wisdom from the perspective of educational phenomenology. *Teach. Educ. Res.* **2024**, *36*, 71–77. Available online: https://d.wanfangdata.com.cn/periodical/Ch9QZXJpb2RpY2FsQ0hJTmV3UzIwMjQxMTA1MTcxMzA0EhFnZHNmanl5ajIwMjQwMTAxMRoIYjZ5dTZsazc%3D (in Chinese).
19. Adhami, N.; Moore, L.R. Intelligent tutoring systems in language learning: A systematic review of pedagogical design and learner impact. *TechTrends* **2025**. [CrossRef].
20. Tighe, A.L.; Sommer, E.T.; Sabol, J.T.; et al. A family-centered approach to learning English as a second language: A mixed-methods experimental evaluation. *Educ. Eval. Policy Anal.* **2025**, *47*, 1093–1112.
21. Špruk, J.N.; Žnideršič, K.; Marolt, M.; et al. *LingoVerse*: Virtual language learning through gamification. *Virtual Real.* **2025**, *29*, 174.
22. Fox, J.; Sanders, K.; Kim, S.H. The Impact of Language Status on Pharmacy Admissions: A Comparative Study of English Language Learners and Native English Speaking Students. *Am. J. Pharm. Educ.* **2025**, *90*, 101904.
23. Li, X.J.; Li, Y.; Wang, J.J. Cognition and re-representation of "student" identity in educational phenomenology. *J. Yuxi Norm. Univ.* **2022**, *38*, 98–102. Available online: https://d.wanfangdata.com.cn/periodical/Ch9QZXJpb2RpY2FsQ0hJTmV3UzIwMjUwMTE2MTYzNjE0EhF5eHNmeHl4YjIwMjIwMTAxMhoINTc2Nmh2MWU%3D (in Chinese).
24. Alexander, C.-T.; Melissa, W.; Elena, P. Determining the diagnostic accuracy of the test of integrated language and literacy skills for college students. *Am. J. Speech Lang. Pathol.* **2023**, *33*, 1051–1058.
25. Yu, X.; Wang, Y.; Liu, F. Language learning motivation and burnout among English as a foreign language undergraduates: The moderating role of maladaptive emotion regulation strategies. *Front. Psychol.* **2022**, *13*, 808118.
26. Su, H.; Ma, F. Language acquisition and cultural identity among modern Chinese minority college students. *Theory Pract. Lang. Stud.* **2021**, *11*, 1203–1216.
27. Jeong, H.; Joe, I. An AI-Based Risk Analysis Framework Using Large Language Models for Web Log Security. *Electronics* **2025**, *14*, 3512.
28. Lukmanjaya, W.; Butler, T.; Cox, S.; et al. Leveraging AI to Investigate Child Maltreatment Text Narratives: Promising Benefits and Addressable Risks. *JMIR pediatr. Parent.* **2025**, *8*, e73579.
29. Chateau, A.; Molle, N.; Yibokou, S.K. Does an autonomising scheme contribute to changing university students' representations of language learning? *Lang. Learn. High. Educ.* **2025**, *15*, 131–144.
30. Zevallos, S.S.N.; Aranzábal, C.F.D.; Ramírez, A.D.C.; et al. Psychometric properties of the strategy inventory for language learning in Peruvian university students. *Front. Educ.* **2025**, *10*, 1562101.
31. Byrne, S.; Bertran, A.; Isanta, T.A. Continuity and change: Language ideologies of Catalan university students. *J. Multiling. Multicult. Dev.* **2024**, *45*, 3995–4010.
32. Shang, T. Research on college students' autonomous English learning in the context of mobile-assisted language learning. *Engl. Square* **2024**, *12*, 74–77. Available online: https://qikan.cqvip.com/Qikan/Article/Detail?id=7111954340 (in Chinese).
33. Mirsanjari, Z. AI-driven vs. Traditional language assessment: Effects on Iranian EFL learners' motivation, anxiety, and proficiency in a high-stakes exam context. *Lang. Test. Asia* **2025**, *15*, 70.
34. Michele, S. Scientific phenomenology in design pedagogy: The legacy of Walter Gropius and Gestalt psychology. *Int. J. Art Des. Educ.* **2021**, *40*, 99–107.
35. Mega, M.W.; Tuti, B.; Novri, S. Free education as superstructure: Phenomenological study of free private education. *Masy. Kebud. Polit.* **2019**, *32*, 217–2226.
36. Wang, N.; Zhou, R.; Liu, C.; et al. Language use in Chinese university students with depressive symptoms.

PsyCh J. **2025**, *14*, 715–717.
37. Zhang, J. Research on college students' attitudes toward computer-assisted language learning. *West. Qual. Educ.* **2023**, *9*, 119–122. (in Chinese).
38. Agustín, G.H.L.D.; Pablo, H.R.; Rodríguez, I.P.; et al. The pedagogy of death and special needs education: A phenomenological study. *Eur. J. Spec. Needs Educ.* **2022**, *37*, 747–760.
39. Fermín-González, M.; Domínguez-Garrido, M.C. A phenomenological approach to intercultural initial education. *Intercult. Educ.* **2021**, *32*, 624–648.
40. Alghamdi, A. Investigating the effectiveness and typology of teachers' interactional feedback in supporting digital game-based language learning. *Front. Educ.* **2025**, *10*, 1645840.
41. Mallina, R.; Shareef, B. XBusNet: Text-Guided Breast Ultrasound Segmentation via Multimodal Vision–Language Learning. *Diagnostics* **2025**, *15*, 2849.
42. Gong, B.; Lin, S. School education from the perspective of phenomenological pedagogy: By Ping Wang, Beijing, China Social Science Press, 2020, 228 pp., RMB 76.00 (paperback), ISBN: 978-7-5203-6395-2. *Asia-Pac. J. Teach. Educ.* **2023**, *51*, 499–501. [CrossRef].
43. Li, Q.; Fu, Y. School education from the perspective of educational phenomenology: By Ping Wang, Beijing, China Social Science Press, 2020, 228 pp., RMB 76.00 (paperback), ISBN 978-7-5203-6395-2. *Asia Pac. J. Educ.* **2023**, *43*, 324–326, [CrossRef].
44. Strohmayer, U. Beyond the Flâneur: Urban walking as peripatetic phenomenological pedagogy. *GeoHumanities* **2023**, *9*, 78–101.
45. Allen, W.J.; Wilkinson, D.; Savulescu, J. When Is It Safe to Introduce an AI System into Healthcare? A Practical Decision Algorithm for the Ethical Implementation of Black-Box AI in Medicine. *Bioethics* **2025**, *40*, 61–72.
46. Männistö, P.M.; Moate, J. A phenomenological research of democracy education in a Finnish primary-school. *Scand. J. Educ. Res.* **2024**, *68*, 1025–1038.
47. Wang, L.J. Research on improving college students' language literacy in the context of artificial intelligence. *Jiaying Lit.* **2025**, *6*, 143–145. (in Chinese).
48. Jonnala, S.; Parida, P.K.; Thomas, N.M. EU AI Act Underrepresented and Insufficient to Address the Risk and Vulnerabilities of Generative AI. *Int. J. Bus. Anal.* **2025**, *12*, 1–27.
49. d'Agnese, V. Being-in-TikTok: A phenomenological analysis of attention, temporality, and education. *Ethics Educ.* **2025**, *20*, 92–106.
50. Matikainen, M. Transformative way of becoming a teacher: A phenomenological-hermeneutic analysis of class teacher education in Finland. *J. Transform. Educ.* **2024**, *22*, 379–396.

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