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From AI Tools to Learner-Centered Human–AI Collaboration: Developing and Evaluating the Learner-Centered Human–AI Pedagogical Framework (LCHAP)

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Abstract—Generative artificial intelligence (AI) is reshaping higher education, yet practical guidance for integrating it into meaningful learning remains limited. This paper introduces the Learner-Centered Human–AI Pedagogical Framework (LCHAP), which positions AI as a collaborative cognitive partner while preserving learner agency and responsibility. LCHAP was implemented through the Human–AI Learning Cycle (HALC) in a 15-week quasi-experimental mixed-methods study involving 80 first-year undergraduates at the Mongolian National University of Education. At post-intervention, the experimental group showed higher mean scores than the control group in English writing, learner engagement, learner autonomy, AI literacy, reflective learning, and critical thinking. Qualitative evidence indicated a shift from answer generation toward idea exploration, comparison, revision, and reflection. Because the reported quantitative evidence is descriptive, the findings should be interpreted as preliminary rather than causal. LCHAP offers a practical design framework for responsible, learner-centered Human–AI collaboration in higher education.

Keywords—generative AI; Human–AI collaboration; higher education; AI pedagogy; learner agency

I. Introduction

Higher education is changing rapidly as generative artificial intelligence (AI) becomes part of everyday teaching and learning. Large language models are increasingly used to support writing, language learning, assessment, and feedback [1], [2]. Their widespread adoption has also raised important questions about learner agency, critical thinking, academic integrity, and the evolving roles of teachers and students. The central challenge is therefore not simply whether AI should be used, but how it can be integrated to support meaningful learning.

International guidance emphasizes that AI should strengthen, rather than replace, human agency through responsible educational practice [3], [4]. However, research has more often evaluated individual tools or isolated outcomes than explained how teachers, learners, and AI can work together within a coherent learning design [7], [11]–[16].

This paper proposes the Learner-Centered Human–AI Pedagogical Framework (LCHAP), which positions AI as a collaborative cognitive partner while keeping learner agency at the center of learning. The framework is operationalized through the Human–AI Learning Cycle (HALC) and examined through a 15-week quasi-experimental mixed-methods study. The study asks whether the LCHAP intervention is associated with favorable learning outcomes and how students engage with AI during the learning process.

II. Related Work

Generative AI may support academic writing, language learning, personalized feedback, and learner engagement [1], [2]. At the same time, dependence on AI-generated content may weaken critical engagement and create challenges for academic integrity and learner responsibility [3]–[5]. These tensions make pedagogical design, not merely tool access, central to responsible integration.

Learner-centered education emphasizes agency, self-regulation, reflection, and active knowledge construction [6]–[10]. Formative assessment research likewise highlights the value of feedback that helps learners monitor and regulate their own learning [12], [13]. Recent studies conceptualize Human–AI interaction as collaboration in which AI supports ideation, dialogue, feedback, and revision while learners retain responsibility for judgment and decision-making [14]–[16].

LCHAP integrates these complementary strands into a single pedagogical framework. Its distinctive contribution is to connect learner agency, responsible AI literacy, reflection, self-regulation, and multi-source feedback through a repeatable classroom cycle.

A central issue in current AI-supported learning is the difference between assistance and substitution. When

generative AI is used mainly to produce finished answers, learners may bypass the processes of planning, evaluating evidence, revising, and explaining their own decisions. By contrast, a learner-centered design can use AI to make these processes more visible: students can externalize initial ideas, interrogate alternative explanations, compare generated suggestions with disciplinary knowledge, and justify why particular revisions are accepted or rejected. This orientation is consistent with agentic and self-regulated views of learning, in which learners actively set goals, monitor progress, and exercise judgment rather than simply receive information [7], [8].

Reflection and feedback are therefore especially important in Human–AI learning environments. Reflective practice emphasizes examining both action and reasoning, while formative assessment research shows that feedback is most productive when learners use it to regulate subsequent performance [11]–[13]. Generative AI can increase the immediacy and volume of feedback, but immediacy alone does not guarantee learning quality. Students still need opportunities to verify claims, compare AI feedback with teacher and peer feedback, identify uncertainty or bias, and decide how to revise their work. LCHAP addresses this need by embedding AI interaction within a broader cycle of independent thinking, critical evaluation, multi-source feedback, and reflection rather than treating the AI response as the endpoint of a task.

III. The Learner-Centered Human–AI Pedagogical Framework (LCHAP)

LCHAP was developed to support the meaningful integration of generative AI into higher education. Rather than treating AI as a substitute for teaching or learning, it frames AI as a cognitive partner that can support inquiry, reflection, and knowledge construction while learners retain responsibility for goals, evidence, and final decisions.

The framework integrates six dimensions: learner agency, Human–AI collaboration, reflective learning, self-regulated learning, multi-source formative feedback, and responsible AI literacy. Together, these dimensions encourage learners to question AI output, compare it with other evidence, revise their work, and reflect on both the learning process and the ethical use of AI [3], [4], [12], [13].

For classroom implementation, HALC guides learners through an authentic task, independent thinking, Human–AI dialogue, critical evaluation, revision with multi-source feedback, and reflection with self-regulation (Fig. 1). The teacher designs and facilitates the task, provides ethical guidance, and supports feedback. Generative AI supplies prompts, alternative perspectives, and immediate feedback, but does not replace learner judgment.

The sequence is deliberately designed to preserve learner ownership. The independent-thinking stage requires students to formulate a preliminary position before consulting AI, reducing the likelihood that the first generated response will anchor their reasoning. During Human–AI dialogue, students may request examples, counterarguments, clarification, or alternative formulations, but they are expected to treat these outputs as provisional. The critical-evaluation stage then shifts attention from fluency to evidence: learners examine relevance, accuracy, consistency, and possible limitations before deciding what to use. Revision incorporates teacher, peer, and AI feedback, while the final reflection stage asks learners to account for what changed, why it changed, and what they would do differently in a subsequent task.

These stages also clarify the complementary roles of the three participants in the learning environment. The learner remains the primary decision-maker and author of the final work. The teacher is responsible for task design, scaffolding, assessment criteria, and ethical expectations, including appropriate disclosure and verification of AI-supported work. The AI system functions as a responsive resource for dialogue, idea generation, explanation, and formative feedback. This role distribution is important because it prevents technological capability from being confused with pedagogical authority. In LCHAP, AI can extend the range and speed of support available to students, but responsibility for interpretation, evidence, and academic decisions remains human [3], [4], [14]–[16].

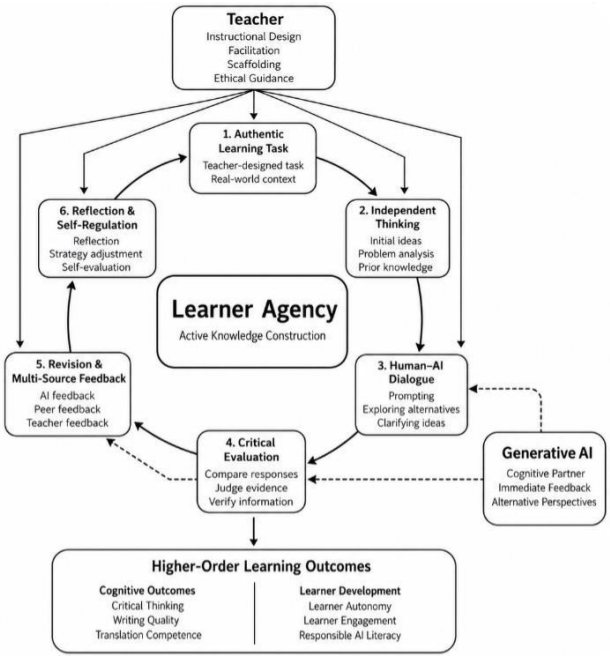


Fig. 1. Human–AI Learning Cycle (HALC)

IV. Research Methodology

The study employed a quasi-experimental mixed-methods design during the Spring 2025–2026 semester at the Mongolian National University of Education. Participants were 80 first-year undergraduates enrolled in compulsory English courses. Two intact classes participated: 40 students in the experimental group and 40 in the control group. The use of intact classes means that group equivalence and causal attribution cannot be assumed.

The intervention lasted 15 weeks. Both groups followed the same curriculum and learning objectives. The experimental group completed LCHAP activities through HALC: students first developed ideas independently, engaged in AI-supported dialogue, evaluated AI output, revised their work using feedback, and reflected on their learning. The control group received the existing instructional approach.

Implementation focused on repeated use of the same learning logic rather than one-time exposure to an AI tool. Across course tasks, students in the experimental group were expected to begin with their own ideas, document or discuss their interaction with AI, evaluate the usefulness of

generated content, revise on the basis of more than one source of feedback, and reflect on the learning process. The design therefore emphasized process as well as product. This repeated structure was intended to help students develop routines for responsible AI use that could transfer across writing and language-learning tasks. The control group completed comparable curricular work without the structured HALC sequence, allowing the study to examine whether the framework was associated with different post-intervention patterns while keeping the formal course objectives consistent.

Quantitative data included pre- and post-intervention measures of English writing performance, learner engagement, learner autonomy, AI literacy, reflective learning, and critical thinking. Qualitative evidence came from classroom observations, reflective journals, learning artifacts, and semi-structured interviews. The present paper reports post-intervention descriptive statistics and a thematic synthesis of the qualitative evidence. No statistical significance or causal effect is claimed from the descriptive comparisons presented here.

V. Results

At post-intervention, the experimental group had higher mean scores than the control group across all six outcomes (Table I). The observed mean differences were 0.39 for AI literacy, 0.32 for reflective learning, 0.26 for learner engagement, 0.24 for learner autonomy, 2.80 points for English writing, and 0.18 for critical thinking. Because these outcomes were measured on different scales, the raw differences should not be compared directly in magnitude. They are descriptive between-group differences and should not be interpreted as evidence of statistical significance.

TABLE I. Descriptive Post-Intervention Outcomes

Outcome	Experimental M ± SD	Control M ± SD
English writing	78.6 ± 6.4	75.8 ± 6.7
Learner engagement	4.12 ± 0.48	3.86 ± 0.51
Learner autonomy	4.05 ± 0.46	3.81 ± 0.49
AI literacy	4.18 ± 0.42	3.79 ± 0.47
Reflective learning	4.09 ± 0.44	3.77 ± 0.50
Critical thinking	3.97 ± 0.51	3.79 ± 0.53

Note: Experimental group n = 40; control group n = 40. Values are mean ± standard deviation.

The qualitative evidence complemented the descriptive pattern. Classroom observations, reflective journals, learning artifacts, and interviews suggested that students gradually moved beyond using AI primarily to generate answers. They increasingly used it to explore ideas, compare perspectives, revise written work, and support reflection. This pattern is consistent with more purposeful Human–AI collaboration, although the qualitative findings should be interpreted within the single-institution context.

Across the qualitative sources, the change was most visible in how students described and enacted the purpose of AI use. Early use tended to emphasize obtaining a response quickly, whereas later learning artifacts and reflections more often showed AI being used as a source of alternatives that still required learner judgment. Students compared suggestions, reworked wording, reconsidered organization, and used feedback to identify gaps in their own drafts. The classroom evidence also suggested that the structured requirement to evaluate and reflect made the decision process more explicit. These observations do not quantify the frequency of particular behaviors, but they help explain how the framework may have supported the descriptive gains reported in Table I.

VI. Discussion

The findings suggest that LCHAP may help shift students' use of AI from simple answer generation toward more active, learner-centered engagement. The stronger patterns observed in AI literacy and reflective learning are especially relevant because both are central to the HALC process. This provides initial support for the framework, although the results should not be interpreted as causal because the study used intact classes and did not report inferential statistical analysis.

A key strength of LCHAP is that it clarifies the roles of learners, teachers, and AI. Learners generate ideas, evaluate information, and remain responsible for final decisions; AI supports dialogue, exploration, feedback, and revision; and teachers design tasks, guide critical evaluation, and establish ethical expectations. This balance allows students to benefit from generative AI without relying on it uncritically. Recent experimental evidence also suggests that guidance-based ChatGPT use can better support self-regulated learning and higher-order thinking than direct-answer use [17].

The findings also support a broader view of AI literacy. It involves more than accessing AI tools or writing effective prompts. Students also need to recognize the limitations of AI-generated content, evaluate its accuracy and relevance, compare it with other evidence, and make responsible decisions about its use. In this sense, AI literacy is closely connected with critical thinking, learner autonomy, and responsible decision-making [3], [4].

For instructors, LCHAP offers a practical way to integrate generative AI into existing teaching without making AI itself the main learning objective. A writing or language task, for example, can begin with independent work, followed by focused AI interaction, evaluation of AI suggestions, revision using multiple sources of feedback, and reflection on the decisions made. This may be particularly useful for first-year students who are still developing academic habits. At the same time, effective implementation requires teachers to design tasks that reward reasoning, define clear boundaries for AI use, and assess both the final product and the learning process [4].

The results should nevertheless be interpreted cautiously. The higher post-intervention means in the experimental group are consistent with the assumptions of LCHAP, but they do not show that the framework alone caused the differences. The study therefore provides a pedagogical framework, an implementation model, and preliminary empirical evidence. Future research should examine LCHAP through stronger baseline-adjusted analyses, validated measures, implementation-fidelity data, and closer investigation of how specific HALC practices relate to learning outcomes.

VII. Pedagogical Implications

Three pedagogical implications follow from the framework. First, institutions should distinguish permitted AI use from pedagogically productive AI use. Policies on disclosure and academic integrity are necessary, but they do not by themselves ensure meaningful learning. Second,

assessment should make the learning process visible by requiring students to explain how AI was used, justify which suggestions were accepted or rejected, and show evidence of revision and reflection. This emphasis on process is increasingly important because recent evidence indicates that even authentic written assessments can remain vulnerable to generative AI and that assessment design must therefore move beyond reliance on the final product alone [18]. Third, teacher development should address not only technical use of AI tools but also task design, verification strategies, feedback literacy, and ethical decision-making [4].

Because LCHAP is organized as a repeatable cycle rather than a platform-specific procedure, it can in principle be adapted as AI systems change. The stable element is not a particular tool but the sequence of independent thinking, guided Human–AI interaction, critical evaluation, revision, and reflection. This design principle is consistent with evidence that scaffolded, guidance-based AI use can support self-regulation, higher-order thinking, and knowledge construction more effectively than unrestricted answer generation [17].

A further implication concerns the relationship between learning design and institutional governance. Clear institutional rules can define acceptable and unacceptable uses of generative AI, but course-level pedagogy must translate those rules into concrete learning practices. LCHAP offers one way to connect governance with classroom action by making learner responsibility, teacher mediation, verification, and reflective use explicit within the learning cycle. In this sense, responsible AI integration is not only a matter of compliance; it is also a question of developing the human capacities needed to use AI critically, ethically, and purposefully [4].

VIII. Conclusion and Limitations

This study introduced LCHAP and operationalized the framework through HALC. Following the 15-week intervention, the experimental group showed higher post-intervention means across all six reported outcomes, while the qualitative evidence indicated more purposeful uses of AI for exploration, comparison, revision, and reflection. These findings provide a preliminary empirical basis for further evaluation of the framework rather than evidence of a causal intervention effect.

The study has several important limitations. It involved two intact classes at a single institution, the sample was modest, and the quantitative evidence reported here is descriptive. The observed group differences may therefore reflect baseline or contextual factors in addition to the intervention. Future studies should report evidence of measurement validity and reliability, conduct baseline-adjusted inferential analyses with effect sizes and confidence intervals, and document implementation fidelity. Replication across disciplines, institutions, and learner populations will be necessary before stronger conclusions can be drawn about the effectiveness or generalizability of LCHAP.

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