

GENERATIVE AI AND THE DEEPENING OF UNDERSTANDING: A HUMAN-AI CO-THINKING MODEL FOR HIGHER EDUCATION

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Abstract

Generative AI (GenAI) is rapidly entering higher education, yet research often foregrounds risk (outsourcing cognition, plagiarism) or efficiency rather than how students use GenAI while learning. This qualitative study examines GenAI use in a liberal-arts course that paired in-class instruction with structured, out-of-class GenAI-supported reflection. After two sessions on the contemporary Kurdish question, 45 students submitted reaction papers describing how they consulted GenAI to deepen partial understanding, clarify confusion, and pursue self-generated questions without copying outputs. Inductive thematic analysis identified three recurrent functions: perspective structuring (mapping competing frames), causal clarification (probing sequences and interdependencies), and conceptual extraction (stabilising key terms before forming arguments). Reported learning gains depended on verification practices that compared AI responses with course materials and instructor cues. The paper proposes a Human–AI Co-Thinking Model that links these practices to scholarship on technology-supported education, instructor role transformation, and shifting norms of authorship, and it derives implications for instructional design, assessment, and accountable GenAI use.

Keywords: *Generative AI, deep understanding, higher education, human-AI collaboration, instructional design.*

1. Introduction

The rapid diffusion of generative artificial intelligence (GenAI) in higher education has blurred familiar lines between studying and producing, learning and composing, assistance and substitution. Institutional responses often polarise between risk and promise, but these debates can obscure a basic empirical question: when GenAI is integrated explicitly into a learning task, what do students actually do with it?

Liberal-arts learning aims at more than surface competence: students are expected to build structured understanding of unfamiliar conceptual systems and complex causal dynamics, then articulate a reasoned position. The contemporary Kurdish question provides a demanding case because it requires multi-perspectival reasoning across competing political narratives and historically layered causal claims.

This paper examines student reflections from a course design that combined online in-class engagement with structured, out-of-class GenAI consultation. Students were instructed to use GenAI not to generate substitutive answers but to deepen partial understanding, clarify confusion, and develop self-generated questions.

The paper's contribution is twofold: it offers an empirically grounded account of learning-oriented GenAI use in this instructional design and proposes a Human–AI Co-Thinking Model that connects these practices to scholarship on technology-supported education, changing instructor roles in GenAI environments, and shifting norms of authorship and originality (Gülbeyaz, 2014, 2026a, 2026b). It further outlines implications for instructional design and assessment in contexts where accountable GenAI use depends on making verification and transformation practices visible and non-optional.

2. Theoretical framing

2.1. Education as technology-supported by design

A useful starting point is to treat “technology-supported education” not as a recent add-on, but as a constitutive condition of organised education. Educational media do not merely provide new tools; they

reconfigure the organisation of learning itself, including roles, authority structures, and what counts as knowledge. From this historical lens, GenAI is legible as a further medium shift – continuous with earlier transformations from scribal practices to print and networked digital environments – yet with a distinctive feature: it competes not only with the teacher’s tools, but with core functions involved in the production, structuring, and legitimisation of knowledge. This intensifies the need to specify what instructors do – and should do – once a powerful para-instructor enters the learning ecology (Gülbeyaz, 2014, 2026b).

2.2. The instructor in a GenAI-equipped learning environment

Recent theorisation of teaching under GenAI conditions suggests a shift from a figure who monopolises answers to one who governs an ecology of inquiry. Rather than serving primarily as the producer and distributor of validated knowledge, the instructor’s redesigned functions include: (i) curating relevance, (ii) moderating “error ecologies” (patterned ways misinformation, over-generalisation, and bias propagate within a learning environment), and (iii) establishing meta-rules – a “control grammar” – that make visibility, provenance, transformation, and cross-checking explicit.

This shift builds on a longer logic of distributing pedagogy across designed architectures. Classical intelligent tutoring systems, for example, already locate instruction in a modular system (e.g., student model, expert model, curriculum/diagnosis, and communication modules). GenAI effectively turns “communication” into an always-on, scalable, persuasive layer. In such conditions, the instructor’s core job is less to supply answers than to engineer and enforce the conditions under which answers can legitimately count as knowledge (Wang et al., 2021; Gülbeyaz, 2026b).

The concept of control grammar is especially important where students can generate plausible text at scale. If GenAI makes production easier, then integrity cannot be reduced to prohibition; it becomes a design question. A control grammar can therefore require students to document prompts, describe how outputs were transformed, and demonstrate verification steps against course materials and other warranted sources. In this framing, the point is not surveillance but an explicit epistemic discipline: students learn the rules by which AI-supported work becomes academically accountable (Gülbeyaz, 2026b).

2.3. Authorship, originality, and the politics of intellectual ownership

A third strand concerns how GenAI destabilises inherited codes of authorship and ownership. Conventional academic regimes treat text as a traceable product of a single author, and originality as an individual property. Yet “intellectual ownership” is historically contingent, bound to modern ideas of individual authorship and originality that emerged comparatively late. Generative systems sharpen these tensions because machine-mediated production complicates how we attribute agency, labour, and credit.

In practice, this is experienced through at least three frictions: (i) GenAI produces text that is neither quotation nor transparent paraphrase; (ii) it makes “style” and “structure” replicable at low cost; and (iii) it encourages iterative co-production in which student agency is distributed across prompts, selections, and revisions. As a result, plagiarism policies that assume a binary opposition (original vs copied) become harder to apply, and the ethical focus shifts towards transformation and attribution: how students can responsibly rework AI-mediated material while making their own epistemic agency visible. The productive response is not to abandon integrity norms but to specify them in ways that match the new production ecology – so that academic ethics becomes something taught through design rather than inferred privately (Gülbeyaz, 2026a).

3. Research design

3.1. Course context and instructional design

Data were collected in a university liberal-arts course that combined online in-class instruction with structured, out-of-class reflection. The task positioned GenAI as a reflective partner in relation to instructor-provided materials (slides, short readings, and guiding questions). Students consulted GenAI in two designated ways: (i) to deepen partial understanding and (ii) to clarify points of confusion. Copying GenAI outputs into the reaction paper was explicitly prohibited.

3.2. Data and analysis

The dataset comprises 45 student reaction papers submitted after the two sessions. For analysis, submissions were reorganised into structured sheets that made (a) prompt content and (b) accompanying meta-reflections traceable during coding. These sheets were derived directly from the original submissions and preserved the distinction between the two task-specified prompt-types.

The corpus was analysed inductively through an iterative thematic analysis in four passes: (1) open coding of statements describing GenAI use; (2) axial grouping into broader functional clusters; (3) comparative validation across prompt-types and across cases; and (4) model building to link emergent

practices (as evidenced in students' written reflections) to the study's theoretical framing. The analysis foregrounds recurring functions and design-relevant mechanisms.

4. Findings: How students used GenAI to deepen understanding

In the “deepen” phase of the assignment, students used GenAI primarily to organise competing perspectives, elaborate causal accounts, and stabilise key concepts for subsequent argumentation. In this sense, conversational systems can support inquiry-oriented learning when used as dialogic resources rather than answer generators (Chan & Pawlina, 2020). Three recurring functions were identified: perspective structuring, causal clarification, and conceptual extraction.

4.1. Perspective structuring: Mapping competing frames

A prominent pattern was using GenAI to map or contrast competing perspectives in the Kurdish question. Students asked GenAI to summarise how different actors – states, ethnic groups, and international organisations – frame Kurdish autonomy in terms such as security threats, territorial integrity, or self-determination. In their reaction papers, students often reported that GenAI helped them “see the structure” of arguments rather than decide which argument is correct.

Perspective structuring refers to using GenAI to generate a provisional map of frames and then using that map to organise one's own reading of course materials. Students described that comparative summaries made it easier to locate the instructor's lecture points and understand why the same event can be interpreted differently by different parties.

A recurrent limitation noted by students was that GenAI sometimes “balanced” perspectives too neatly or produced generic summaries, which could flatten asymmetries in power, history, or normative stakes.

4.2. Causal clarification: Probing sequences and interdependencies

A second recurring pattern involved using GenAI to clarify causal sequences – what led to what, which actors reacted, and how decisions produced unintended consequences. For the Kurdish question, causal chains are historically layered, spanning imperial collapse, border settlements, state formation, repression–resistance cycles, regional wars, and shifting alliances.

Students used GenAI to ask questions such as: “What events intensified Kurdish nationalism?” “How did the Iraq War reshape Kurdish autonomy?” and “Why did certain regional governments shift policy?” In their accounts, this appeared as a move from “I heard about X” to “I can explain how X relates to Y.” Causal clarification, in this sense, is the use of GenAI to elaborate linkages across dispersed facts into an interpretable narrative.

Many students described iterative querying (timelines → exceptions → disagreements → comparison with course materials), suggesting that deepened understanding depended less on any single response than on sustained questioning and cross-checking. This resembles self-regulated learning patterns that combine cognitive strategies (e.g., elaboration and organisation) with metacognitive control (e.g., goal setting and self-monitoring) (Pinkwart & Liu, 2020).

4.3. Conceptual extraction: Stabilising key terms before arguing

A third pattern involved using GenAI to extract and stabilise core concepts needed for analysis and argument. Students frequently reported uncertainty about terms such as nation, ethnicity, statelessness, sovereignty, self-determination, minority rights, and security dilemmas.

GenAI was used to obtain definitions, distinctions (e.g., “nation vs state”), and illustrative examples. Students then used these clarified concepts to re-read lecture points and craft their own claims. Conceptual extraction refers to this scaffolding move: establishing workable meanings that enable more coherent reasoning. Students also recognised that GenAI definitions could be overly broad or “textbook-like” and therefore required refinement to fit the course's risk-society framing.

Across all three functions, reported learning gains depended on verification and calibration practices. Students compared GenAI outputs with lecture slides, readings, and instructor cues; requested counter-arguments or alternative framings; and adjusted what they retained for relevance and specificity. Where GenAI use supported deeper understanding, they treated it as one voice among several and maintained agency through selection, revision, and triangulation rather than accepting outputs as final authority. The next section turns to the complementary “ask” use case: how students used GenAI to articulate and work through what they did not understand.

5. Findings: Asking what was not understood

The second major use case – explicitly required by the assignment – was asking GenAI about what students did not understand. In these accounts, GenAI functioned as a low-stakes, immediate tutor that reduced the friction of admitting confusion and enabled students to continue inquiry after class.

5.1. Question externalisation: Turning vague confusion into explicit questions

Many students initially described uncertainty in vague terms (e.g., “I don’t get why ...”, “I’m not sure what this means ...”). Through interaction with GenAI, these confusions were often reformulated into more explicit, tractable questions. For instance, a starting question such as “Why do Kurds not have a state?” could be refined into more targeted lines of inquiry (e.g., which treaties and state-formation processes impeded Kurdish statehood, or how international norms frame self-determination claims).

This process can be termed question externalisation: using GenAI to articulate and structure uncertainty. The educational value lies less in a final answer than in converting diffuse confusion into a set of workable inquiries that can be pursued through course materials.

5.2. Error exposure and correction: Discovering misconceptions

A further benefit reported by students was identifying and correcting misconceptions. Some accounts describe how GenAI exchanges made internal diversity visible (geographic, political, and linguistic), while others note that the interaction helped disentangle confluences across state contexts (Turkey, Iraq, Syria, and Iran).

At the same time, students’ reflections indicate that GenAI can generate misconceptions as easily as it resolves them. In the more productive cases, students treated GenAI as one provisional source and calibrated it through the verification routines described in Section 4.3 (e.g., checking against slides, readings, and instructor cues).

5.3. Transition to personal positioning

For a liberal-arts reaction paper, the endpoint is not only comprehension but a reasoned stance. Many papers suggest a trajectory in which clarification of confusion supports subsequent organising moves (e.g., mapping perspectives and stabilising concepts) that enable students to articulate their own position. GenAI appears to support this transition when students maintain agency through selection, rejection, and reframing rather than adopting outputs as ready-made conclusions.

6. Discussion and implications

6.1. Re-reading “technology-supported education” under GenAI

Drawing on the usage patterns described in Sections 4–5, the findings support a media-historical reading of GenAI in higher education: when the dominant educational medium changes, the sites and authorities of explanation tend to shift with it. Students’ reaction-paper traces suggest that GenAI created an additional dialogic space after class in which explanation, comparison, and questioning could continue. This is not simply “more study time” but a relocation of conceptual work – where students organise, test, and refine understanding beyond the classroom encounter (Gülbeyaz, 2014, 2026b).

6.2. The instructor as curator of relevance and moderator of error ecologies

In such an ecology, the instructor’s role does not disappear but is redesigned: less a sole source of answers and more a curator of relevance and a moderator of “error ecologies”. The implications of the present findings are practical: assignments and instruction can reward inquiry over extraction, teach routines of scepticism and triangulation, and treat recurrent GenAI tendencies (genericness, over-neat balancing, variable depth) as explicit objects of teaching rather than invisible failure (Gülbeyaz, 2026b).

6.3. From policing plagiarism to cultivating accountable transformation

When GenAI becomes part of learning, integrity hinges on disclosure and responsible transformation rather than on a simple used/did-not-use binary. This aligns with the view that conventional plagiarism norms rest on historically specific ideas of intellectual ownership that are increasingly destabilised by machine-mediated text production. A control-grammar approach reframes integrity as a design problem: tasks can require students to document prompts and key decision points, show how AI material was revised and integrated with course materials, and reflect on where GenAI helped and where it misled. This shifts evaluation towards verification and synthesis while making provenance visible (Gülbeyaz, 2026a, 2026b).

Taken together, the findings support a Human–AI co-thinking account: deepened understanding arose from students’ active checking, rewriting, and integrating of AI outputs rather than from the outputs themselves. Related computational learning-theoretical work similarly frames AI as a partner that can accelerate inquiry, enable pauses, and support restarts, potentially expanding learners’ agency and metacognitive control. Precisely because GenAI can also smooth over uncertainty and produce persuasive errors, the decisive condition is governance: co-thinking remains epistemically legitimate only when provenance, transformation, and verification are treated as non-optional routines rather than optional good practice (Gibson & Ifenthaler, 2024; Gülbeyaz, 2026b).

6.4. Practical design principles for GenAI-supported deep understanding

Three design principles follow from the model developed in this paper. First, separate “deepen” and “ask” phases so students explicitly work with what they partly understand as well as what remains unclear. Second, require a transformation trace: brief annotations of what was kept, rejected, and reframed (without demanding full chat logs). Third, teach verification as routine: triangulate claims with slides/readings, request counter-arguments or alternative framings, and independently check named facts. Together, these principles operationalise a broader shift – from treating GenAI as a forbidden shortcut to treating it as a site for practising responsible inquiry.

7. Conclusion and limitations

This paper shows how students used GenAI in a structured reflective design as a resource for deepening understanding rather than as a substitute answer generator. The central claim is that learning gains depended less on access to GenAI than on the practices and rules that shaped its use: students benefited when they retained agency through selection and revision and when course design made verification and transformation visible requirements. The Human–AI Co-Thinking Model captures this dynamic by treating GenAI as a dialogic partner in inquiry whose epistemic risks and affordances must be governed through explicit meta-rules.

This qualitative study is situated in one course context and relies on reaction-paper traces rather than full interaction logs, which limits fine-grained analysis of turn-by-turn dialogue and the timing of verification. Future work could triangulate self-reports with opt-in logs, classroom observation, and longitudinal designs that track how verification routines and transformation practices develop over time. For higher education, the practical task is not to choose between prohibition and uncritical adoption, but to redesign learning ecologies so that students learn to think with – and critically against – GenAI.

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