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Generative AI in Art and Design Education: Keeping the Human in the Creative Loop

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Abstract

Research on generative artificial intelligence in education reveals a persistent divergence between successful assisted performance and the development of independent knowledge, creative judgment, and transferable skill. Studies of art and design additionally identify opportunities for iterative exploration alongside concerns about visual fixation, uncertain authorship, and dependence on generated alternatives. These findings create an instructional problem: educators need to determine which creative decisions should remain with learners, which operations can receive bounded assistance, and which activities can be delegated without bypassing the intended learning. Existing scholarship addresses these questions through research on scaffolding, human-AI collaboration, assessment, and psychological ownership, but these contributions require closer integration within everyday studio practice. This article develops a Process-Centered AI Integration Framework for secondary and postsecondary art and design courses. The framework allocates tasks through three modes, protect, support, and delegate, according to learning objectives and demonstrated evaluative capability rather than the proportion of an artifact generated by AI. Six recursive phases connect intention formation, bounded assistance, comparison of alternatives, purposeful revision, human critique, and reflection with independent transfer. Parallel curricular applications, assessment criteria, and a reusable assignment planner specify retained decisions, appropriate AI roles, and concise evidence of learning. The model addresses the performance-learning distinction by making disciplinary reasoning observable across creative production while treating process ownership, product ownership, and achievement as related but distinct educational concerns.

Keywords: generative artificial intelligence, art and design education, creative agency, process ownership, studio pedagogy, authentic assessment.

1. Introduction

Research on generative artificial intelligence in art and design education increasingly identifies a tension between expanded production capability and the disciplinary learning that creative production is intended to develop (Fang, 2026; Fleischmann, 2026). An accomplished visual artifact can result from sustained observation, experimentation, and judgment, but a similarly polished artifact can also emerge through acceptance of an algorithmically generated solution. The educational distinction concerns the reasoning exercised during production, not simply the appearance of the submitted work. Studio-based research situates artistic development within interconnected practices of observing, envisioning, developing craft, expressing, reflecting, and exploring, rather than within finished products alone (Hetland et al., 2013). Generative systems complicate this relationship by contributing not only execution but also possibilities, interpretations, and proposed revisions that can become central to creative decision-making (Hutson & Cotroneo, 2023). Consequently, secondary and postsecondary art and design courses face an instructional question that extends beyond whether AI should be permitted: which activities must continue to function as opportunities for learning? Addressing this question requires a research-based account of how assistance changes the relationship among creative process, demonstrated understanding, and perceived authorship (Draxler et al., 2024; Hutson, 2025a).

Empirical studies demonstrate that the educational consequences of generative AI depend substantially on the organization of assistance and the outcome being measured (Bastani et al., 2025; Kestin et al., 2025). In secondary mathematics, unrestricted assistance improved supported practice performance while reducing subsequent unaided examination performance relative to a control condition (Bastani et al., 2025). By contrast, a purpose-designed tutor produced larger immediate learning gains than an active-learning comparison in a university physics experiment (Kestin et al., 2025). Research on writing similarly found stronger improvement in assisted essays without corresponding significant advantages in knowledge gain or transfer (Fan et al., 2025). These findings extend the established distinction between performance during instruction and learning demonstrated through retention or transfer (Soderstrom & Bjork, 2015). For creative education, the implication is that artifact quality and productive speed provide incomplete evidence of the capacity to notice formal relationships, evaluate alternatives, or respond to a changed constraint. Instruction therefore needs to preserve opportunities to exercise the target capability while using assistance to make that exercise more accessible, intelligible, and productive.

The creative process introduces a further difficulty because abundant generated alternatives do not necessarily produce broader exploration or stronger independent judgment (Doshi & Hauser, 2024; Wadinambiarachchi et al., 2024). Experimental research on visual ideation identified greater fixation on an initial example under image-generation support than under an unsupported baseline, with image-search support also increasing fixation (Wadinambiarachchi et al., 2024). In a separate creative-writing experiment, AI suggestions improved individual evaluations while making the resulting stories more similar across participants (Doshi & Hauser, 2024). Art-education research nevertheless documents productive uses of iterative prompting when students connect verbal specification, visual comparison, and purposeful adjustment (Hutson & Cotroneo, 2023). Research in secondary art history

likewise places precise visual description and disciplinary vocabulary at the center of effective interaction with generated imagery (Carpino & Hutson, 2024). The contrast suggests that the educational value of generation depends on what learners do with alternatives rather than on the availability of alternatives alone. A usable instructional response must therefore connect exploration to explicit criteria, material or visual testing, and opportunities to revise an emerging intention.

Creative ownership adds a psychological dimension to the instructional problem because influence over an artifact, public authorship, and a feeling of personal connection can diverge (Draxler et al., 2024; Pennanen et al., 2026). Research on AI-assisted writing shows that people may claim authorship without experiencing equivalent psychological ownership, while greater influence over the work can increase ownership (Draxler et al., 2024). More recent experimental evidence indicates that prompting and editing interact in shaping ownership, rather than contributing through a simple additive relationship (Pennanen et al., 2026). These results suggest that neither a prompt count nor a percentage of generated content adequately represents the experience of creative control. For educational purposes, ownership of the process can be examined through perceived influence over goals, criteria, revisions, and stopping decisions, while ownership of the product concerns the relationship to the resulting artifact. These dimensions also need to remain distinct from demonstrated learning, since confidence in authorship does not establish the ability to explain or reproduce a disciplinary decision (Darvishi et al., 2024; Fan et al., 2025). A process-centered approach can address these concerns together by making consequential decisions visible without treating subjective ownership as a grading criterion.

Existing scholarship offers important resources for AI integration but leaves educators with a difficult translation from general principles to individual studio activities (Fang, 2026; Perkins et al., 2024). Constructive alignment connects learning objectives, teaching activities, and evidence of achievement, while formative-assessment research emphasizes active interpretation and use of feedback (Biggs, 1996; Nicol & Macfarlane-Dick, 2006). The Artificial Intelligence Assessment Scale relates permitted AI use to assessment purposes, and scaffolded integration emphasizes independent capability alongside progressively expanded assistance (Hutson, 2025b; Perkins et al., 2024). Design-education interviews additionally foreground critical judgment, disciplinary traditions, and institutional conditions as central influences on implementation (Fleischmann, 2026). Across secondary and postsecondary courses, these principles must accommodate variation in prior knowledge, material experience, interpretive fluency, and access to appropriate tools. Educational level alone cannot determine the appropriate degree of delegation, because the relevant capability must be established for the particular task and learning objective. Accordingly, a practical model must combine transparent task allocation with flexible support, accessible participation, and evidence that the targeted reasoning remains available to the learner (CAST, 2024; Miao et al., 2024).

The central gap concerns the integration of task allocation, creative-process instruction, and evidence of independent learning within a single classroom decision structure. Research has established that tool design can influence learning, exploration, and ownership, while educational frameworks have clarified the importance of explicit AI permissions and scaffolded capability (Bastani et al., 2025; Pennanen et al., 2026; Perkins et al., 2024).

What remains insufficiently connected is how an educator translates these findings into retained student decisions at each phase of an art or design assignment. The guiding question is therefore how generative AI can enter creative coursework without replacing the reasoning, experimentation, and evaluative practice specified by the learning objectives. This article addresses that question through a Process-Centered AI Integration Framework that assigns individual tasks to protect, support, or delegate modes. The model connects these modes to six recursive phases: intention formation, bounded assistance, comparison of alternatives, purposeful revision, human critique, and reflection with independent transfer. Through this structure, the proposed model links AI use to observable disciplinary decisions, differentiated studio applications, and assessment evidence that distinguishes a successful artifact from a developing creative capability.

2. Literature Review

2.1 Creative Learning, Studio Practice, and Generative Production

Creative education has long treated making as a form of inquiry in which perception, technical action, interpretation, and reflection develop together. Studio Thinking identifies habits that connect craft and expression with observation, persistence, exploration, and critical reflection, providing a language for describing learning that remains only partly visible in a completed artwork (Hetland et al., 2013). These habits are especially relevant when a tool can produce convincing visual relationships before a learner can explain the principles involved. Scaffolding research in art history similarly shows how a substantial interpretive task can be organized through smaller opportunities to observe, describe, receive feedback, and build an argument (Kutis, 2020). Such approaches locate rigor in the progression of disciplinary activity rather than in an uninterrupted demand for independent production. Within this tradition, a sketch, material trial, annotated comparison, or revised interpretation can function as evidence of developing understanding. Generative assistance changes the available resources for that inquiry, but the curriculum still needs to specify the perceptual, technical, and interpretive work through which learning is expected to occur. The relevant problem is therefore not the presence of mediation but the displacement of activities that carry the intended educational function.

Early research on generative imagery in creative classrooms emphasizes the importance of connecting prompt construction to iterative visual reasoning. Hutson and Cotroneo (2023) describe a classroom process in which students refined ideas through repeated verbal specification and examination of generated images, with attention to both opportunities and ethical concerns. Carpino and Hutson (2024) place a related emphasis on disciplinary vocabulary and formal description in secondary art-history learning. Across these studies, the productive educational activity lies in the comparison between an intended relationship and an observed result, rather than in generation by itself. A recent synthesis of 27 empirical and observational studies identifies a broader imbalance between support for early ideation and support for execution requiring technical nuance, embodied practice, and contextual judgment (Fang, 2026). This distinction matters for art and design courses because understanding materials, spatial relationships, or cultural meanings cannot be reduced to selecting an attractive output. The findings support a curriculum that treats generated material as something to investigate and test. They also suggest that instructional attention must continue through execution, critique, and adaptation rather than ending when an initial concept becomes visually persuasive.

2.2 Assisted Performance, Independent Learning, and Transfer

The distinction between assisted performance and independent learning is central to interpreting educational AI research. Soderstrom and Bjork (2015) show that observable performance during acquisition can diverge from durable learning, particularly when instructional conditions alter the difficulty of retrieval or the availability of support. Bastani et al. (2025) make this distinction concrete in a randomized secondary-school mathematics study: a general-purpose GPT interface and a teacher-configured tutor both increased assisted practice scores. The corresponding estimated increases were 13.7 and 36.1 percentage points, respectively. Subsequent unaided examination performance decreased by 5.4 percentage points in the general-purpose condition, while the tutor estimate of -0.4 percentage points did not differ significantly from the control. Figure 1 displays these estimates and the associated uncertainty. The study illustrates that successful production during assistance can coexist with weaker subsequent performance.

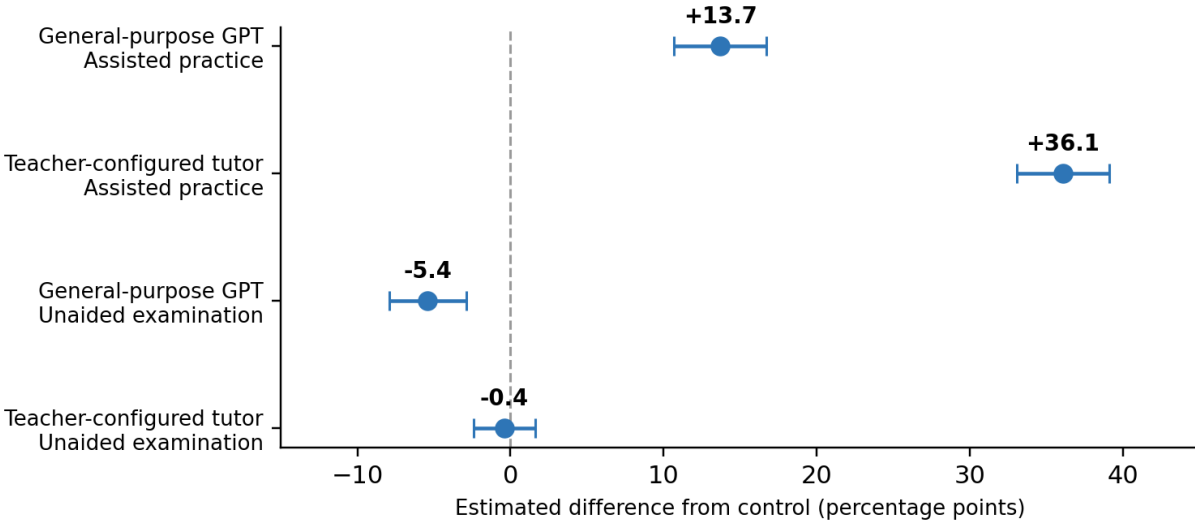


Figure 1. Assisted Practice and Subsequent Independent Performance Can Diverge

Note. Whiskers show ± 1 standard error. Estimates from Bastani et al. (2025); illustrative of the learning-performance problem in that study population, not effect sizes for art and design courses.

For art and design education, the corresponding assessment question is whether the learner can recognize, explain, and adapt the targeted relationship when assistance no longer supplies that particular decision.

Other experimental evidence demonstrates that assistance can support learning when instructional design structures the interaction. Kestin et al. (2025) found stronger immediate learning outcomes with a purpose-designed AI tutor than with an active-learning comparison in an undergraduate physics course involving 194 students. The result concerns a carefully constructed tutoring arrangement, rather than unrestricted access to a general-purpose system. Fan et al. (2025), in a randomized study involving 117 learners, found that ChatGPT support improved essay-score gains without producing significant differences in knowledge gain or transfer. Together, these studies distinguish the availability of AI from the pedagogical conditions under which AI is used. The implication for creative coursework is to identify the activity that carries learning, such as predicting a compositional effect or testing a material choice, before assigning a generative role. Explanations, feedback, and alternative representations may support that activity, whereas supplying the completed disciplinary judgment can remove the opportunity to practice it. A process-centered curriculum therefore needs both productive assistance and a separate means of examining whether the relevant capability has developed.

2.3 Creative Exploration, Fixation, and Iterative Control

Research on creative performance presents a similarly differentiated picture of generative assistance. Doshi and Hauser (2024) found that AI-generated ideas improved evaluations of individual short stories, particularly for participants with lower baseline creativity, while reducing diversity across the resulting collection. Wadinambiarachchi et al. (2024) examined visual ideation in a between-participants experiment involving 60 participants and found stronger fixation under AI-image support than under the unsupported baseline. Image-search support also increased fixation, making the educational issue broader than a simple contrast between algorithmic and conventional resources. The evidence indicates that exposure to visually compelling examples can narrow subsequent exploration when comparison and reframing remain weak. Process-oriented interface research provides a relevant response: a preprint study of 24 participants found that a system separating divergent exploration from convergent refinement supported more novel and diverse images than a linear chat comparison (Wen et al., 2026). Reported agency and ownership nevertheless varied, and the learning evidence primarily concerned self-reports and observed strategy use. These findings support structured exploration while also showing why creative-output measures, subjective experience, and disciplinary learning need distinct forms of assessment.

2.4 Agency, Authorship, and Psychological Ownership

Human-AI authorship research demonstrates that ownership cannot be inferred directly from the amount of visible manual production. Across two studies, Draxler et al. (2024) identified a discrepancy between perceived ownership and public authorship in AI-assisted

text production, with influence over the text contributing to psychological ownership.

This discrepancy, between declaring authorship and experiencing it, points to a distinction worth naming directly: the cognitive act of directing generative output toward an intended result is not the same act as producing that result manually, yet both can be publicly claimed as authorship. Suarez (2026) terms this distinction algorithmic authorship, the exercise of directive judgment over AI-generated material as a form of authorial contribution distinct from, but not reducible to, either full manual production or passive acceptance of AI output.

This distinction is easy to collapse into terms already in circulation, so it is worth being precise about what separates it from them. Co-authorship and AI-assisted authorship both describe a collaborative arrangement, an account of who contributed what to a shared output, and both presuppose at least two contributing parties whose respective shares can, in principle, be identified. Algorithmic authorship describes something narrower and more specific: a cognitive act that a single person performs alone, with no collaborator in the ordinary sense, when they direct a generative system's output toward an intended result through selection, constraint, and revision rather than through manual execution. Creative direction, a term already used in film and design production, comes closer, but it typically describes a supervisory role exercised over other people's manual labor, whereas algorithmic authorship describes a first-person relationship between a single author and a non-human generative process. The distinction matters because Draxler et al.'s (2024) finding, that people self-declare as authors without experiencing equivalent ownership, is otherwise difficult to explain. If directing and producing were the same act, the discrepancy would not exist. Algorithmic authorship names the act that public authorship claims are tracking even when psychological ownership lags behind it.

Figure 2 places this distinction on two axes: the degree to which an artifact was manually produced versus directed into being, and the degree to which its authorship was merely claimed versus actually felt. Full manual creation sits at one corner, where production and felt ownership are both high and rarely in tension. The pattern Draxler et al. (2024) documented, public authorship claimed over AI-generated text without a matching sense of ownership, occupies the corner where directed production combines with low felt ownership, a claim made but not experienced. Passive acceptance of AI output, generation with minimal direction and no meaningful revision, sits at low production and low ownership regardless of what is claimed publicly. Algorithmic authorship occupies the remaining corner: production is directed rather than manual, yet felt ownership remains high because the directive judgment, the selection, the constraint, the revision, was substantively the author's own. This is the quadrant existing terminology has no name for, and the one this framework's protect and support modes are designed to keep populated.

	Low felt ownership	High felt ownership
Manual production	(rare in practice — manual work with disclaimed ownership)	Full manual creation — production and ownership aligned
Directed / AI-assisted production	The AI ghostwriter effect (Draxler et al., 2024) — authorship claimed, ownership not	Algorithmic authorship — directive judgment retained; production delegated, ownership

	felt; or passive acceptance, when direction is minimal	sustained
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Note. Rows distinguish who or what performed the production act; columns distinguish claimed authorship from felt ownership. Algorithmic authorship occupies the cell existing terms (co-authorship, AI-assisted authorship, creative direction) do not clearly name.

Pennanen et al. (2026) extend this work through a preregistered experiment involving 273 participants and comparisons among prompting and editing arrangements. Editing strengthened ownership particularly under single-prompt conditions, while iterative prompting contributed more when editing was unavailable. Fully manual creation produced higher ownership than the AI-assisted arrangements in that study. These findings concern psychological relationships to produced text, but they identify useful variables for educational inquiry: control, opportunity to intervene, and the character of human contribution. Hutson (2025a) similarly argues for distinguishing content generation, structural assistance, creative input, and analytical contribution rather than representing collaboration through a single sliding scale. For art and design education, these distinctions support examining ownership of creative direction separately from attachment to the artifact and separately again from demonstrated knowledge.

Agency also requires more than a stated feeling of control or continued access to helpful feedback. Darvishi et al. (2024) investigated AI-supported peer feedback with 1,625 students across 10 courses and examined what occurred when assistance changed or was withdrawn. The assistance used rule-based and semantic techniques, and the findings indicated reliance on support rather than straightforward internalization of the supported behavior. Replacing automated prompts with self-monitoring checklists only partly compensated for the removal of assistance. This evidence cautions against assuming that adding a reflection form necessarily produces self-regulation. The instructional challenge is to connect reflection to actual decisions and subsequent opportunities to act without the same prompt. Process ownership can therefore be investigated through accounts of intended effects, rejected suggestions, changes in direction, and responsibility for final choices. Such accounts become educationally informative when considered alongside visible work and performance on a related new task, not when treated as substitutes for those forms of evidence.

2.5 Instructional Scaffolding, Assessment, and the Integration Gap

Assessment and instructional-design scholarship provides a basis for translating these findings into classroom decisions. Constructive alignment requires a coherent relationship among intended outcomes, learning activities, and assessment, making the educational function of a task the appropriate starting point for AI allocation (Biggs, 1996). The ICAP framework further distinguishes interaction with materials from constructive activity that generates new explanations and from dialogue that develops understanding through exchange (Chi & Wylie, 2014). Formative-assessment scholarship emphasizes the interpretation and use of feedback rather than the delivery of comments alone (Nicol & Macfarlane-Dick, 2006). More specifically, the AI Assessment Scale supports explicit decisions about permitted AI use in relation

to learning outcomes (Perkins et al., 2024). Scaffolded integration connects expanded AI use with evidence of independent capability and authentic assessment (Hutson, 2025b). These contributions establish why a classroom policy should specify both what assistance may do and what students must still demonstrate. They also leave room for differentiated support: an explanation can help a novice learn a concept before independent mastery, while delegation of the assessed decision requires a different justification.

Research on implementation confirms the importance of teaching conditions rather than tool access alone. Interviews with nine academics across design-education contexts foregrounded critical judgment, prompt literacy, and differences in institutional resources and pedagogical traditions (Fleischmann, 2026). A survey of 500 university design students associated technical and pedagogical support with patterns of AI use and reported design-learning outcomes, although the cross-sectional design does not establish causal improvement in learning (Zhang, 2026). These studies make teacher mediation a substantive part of AI integration rather than an administrative addition. International guidance likewise connects AI capability to human-centered thinking, ethical understanding, and responsible application (Miao et al., 2024). Accessibility guidance emphasizes multiple ways to perceive information, act, communicate, and develop fluency with graduated support (CAST, 2024). Such principles complicate any rule that treats unaided performance as the withdrawal of all assistance. The appropriate distinction concerns whether support supplies the target judgment, not whether a student uses an accessible interface, alternative response mode, or assistive technology.

The literature therefore identifies the components of a solution but does not fully connect them at the level of everyday creative coursework. Learning studies distinguish supported performance from transfer; co-creation research examines exploration and control; ownership studies identify the importance of influence; and assessment frameworks clarify permissible assistance. What remains to be integrated is a task-level structure that links these strands to the recurring decisions of a studio assignment (Fang, 2026; Hutson, 2025a; Perkins et al., 2024; Wen et al., 2026). An educator needs to know what to retain, what to scaffold, what to delegate, what evidence to collect, and when to reintroduce independent practice. The same structure should accommodate secondary and postsecondary courses without equating age, course level, or technical fluency with evaluative expertise. It should also preserve material experimentation and divergent inquiry rather than recast all creative education as curation. The framework developed below addresses this integration gap through task-relative AI modes, recursive creative phases, and coordinated process and transfer evidence. The contribution lies in connecting these decisions within a usable instructional model rather than treating permission, production, ownership, and assessment as separate problems.

3. The Process-Centered AI Integration Framework

3.1 Allocating Assistance by Learning Function

The Process-Centered AI Integration Framework begins with a specific performance of understanding rather than a general policy about AI use. An educator first identifies the relationship that

students should be able to notice, explain, construct, evaluate, or adapt. Examples include explaining how contrast organizes visual attention, testing a relationship between form and function, or interpreting how a material choice changes meaning. The assignment is then decomposed into consequential decisions and supporting operations. Each operation receives a protect, support, or delegate mode according to the intended learning and the capacity to evaluate a resulting output. This approach extends constructive alignment into the organization of human-AI work and retains the multidimensional treatment of contribution developed in prior scholarship (Biggs, 1996; Hutson, 2025a). The unit of allocation is therefore a task or decision, not a student identity, software product, or percentage of generated content. Figure 3 summarizes the allocation logic and the evidence required to revisit a decision.

Protect mode reserves the target decision for direct student performance when generation would replace the practice or evidence specified by the objective. Support mode permits bounded explanations, questions, examples, or feedback while retaining the target reasoning and selection of a response. Delegate mode permits AI to execute a peripheral operation, or a previously demonstrated capability that is not the current assessment target, when the output can be specified and checked. These modes describe different instructional functions rather than a hierarchy in which every learner must progress toward maximum delegation. A novice may receive substantial explanatory support while a technically experienced student may still need protected practice with a new interpretive problem. Conversely, a student with

limited technical fluency may appropriately delegate an incidental formatting operation while demonstrating sophisticated conceptual reasoning. The distinction between explanation and substitution connects evidence on structured tutoring with the emphasis on independently demonstrable capability in scaffolded integration (Hutson, 2025b; Kestin et al., 2025). Across modes, the educator remains responsible for determining whether assistance preserves the relevant opportunity to learn.

The allocation decision remains provisional because creative tasks and learning needs change during a project. A generated variation may reveal an unfamiliar spatial relationship, prompting a return from delegation to guided analysis. A successful comparison or material test may provide evidence that a previously protected operation can become peripheral in a later assignment. For each proposed delegation, the model asks whether the operation is outside the current target, whether the student can specify an acceptable result, and whether checking the result is feasible. When any condition is absent, the response is additional instruction, a bounded support arrangement, or a non-AI route rather than unchecked delegation. This procedure treats assessment evidence as feedback for instructional design, consistent with formative-assessment research (Nicol & Macfarlane-Dick, 2006). It also prevents competent use of one tool from being mistaken for expertise across unrelated disciplinary tasks. The aim is a defensible division of activity in which automation reduces incidental work without removing the decisions through which the intended capability develops.

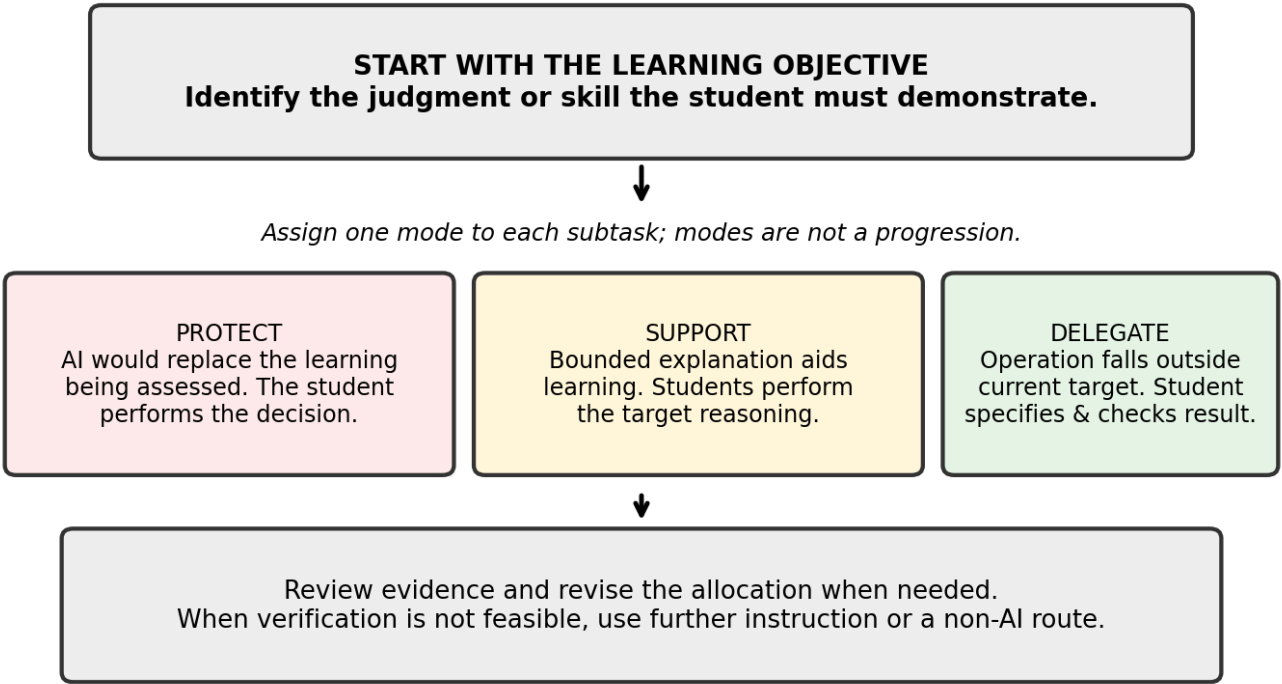


Figure 3. Task-Level Allocation of Protect, Support, and Delegate Modes

Note. Model schematic. Allocation concerns a task and learning objective, not a numerical level of AI use. A protected decision may still receive access support or bounded explanation during learning. When verification is not feasible, use additional instruction or a non-AI route rather than unchecked delegation.

3.2 Six Recursive Phases of Creative Learning

The six phases organize opportunities for disciplinary action rather than prescribe an inflexible chronology. Intention formation establishes a provisional direction; bounded assistance defines a useful role for AI; comparison tests alternatives; revision develops a reasoned response; critique introduces human interpretation; and reflection with transfer examines what remains available beyond the immediate artifact. Creative inquiry may return repeatedly to an

earlier phase when a material discovery, failed experiment, or interpretation changes the problem. This recursive structure preserves the exploratory character of studio learning and the distinction between divergent and convergent activity emphasized in co-creation research (Hetland et al., 2013; Wen et al., 2026). A phase can include protected and supported tasks simultaneously, while delegation remains conditional on the function of the specific

operation. The workflow therefore does not require a complete concept before experimentation or force every assignment to contain a fixed number of prompts. Table 1 specifies retained decisions, possible AI roles, and observable checkpoints. Figure 4 visualizes the cycle and the relationship between process evidence and independent transfer.

Table 1. Six Phases of the Process-Centered AI Integration Framework

Phase	Retained student decision	Appropriate AI role	Evidence and checkpoint
Intention formation	Identify a provisional question, desired relationship, and criteria for progress.	Clarify terms or suggest questions without selecting the final direction.	Initial sketch, observation, or brief explanation; confirm what is being investigated.
Bounded assistance	Specify the help needed and the judgment that remains with the learner.	Explain, question, or provide alternatives within the agreed task mode.	Brief allocation statement; check that support does not supply the target decision.
Comparison of alternatives	Evaluate consequential differences using disciplinary criteria.	Generate contrasting options or support description for student verification.	Annotated comparison; explain why one alternative fits the intention more closely.
Purposeful revision	Predict an effect, intervene, and examine the result; justify retention when appropriate.	Execute constrained changes or suggest possibilities that remain subject to testing.	Before-and-after evidence or a retention rationale; connect choice to consequence.
Human critique	Interpret feedback and decide whether to revise, investigate, or defend.	Provide an additional perspective without replacing peer or educator dialogue.	One critique point and a reasoned response; test coherence between intent and interpretation.
Reflection and transfer	Explain contribution and apply the target capability under a changed condition.	Support organization outside the target judgment; do not supply the transfer response.	Brief reflection plus new performance evidence; distinguish ownership from achievement.

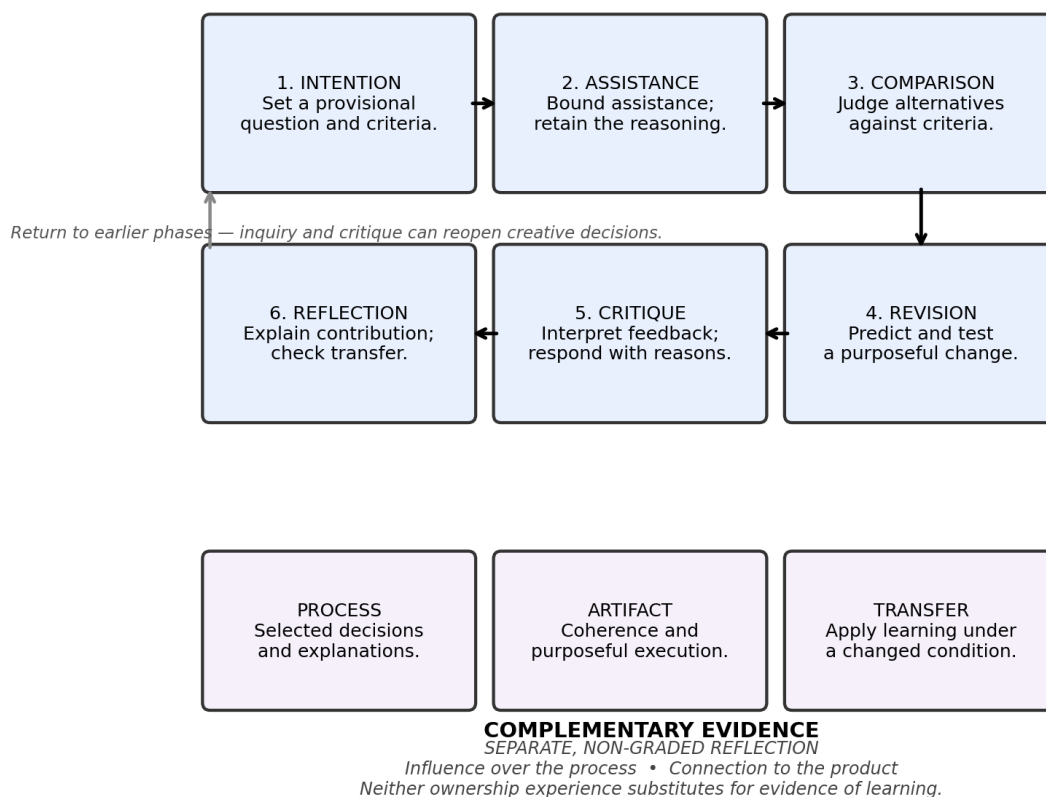


Figure 4. Recursive Creative Process and Complementary Evidence of Learning

3.3 Intention Formation and Bounded Assistance

Intention formation establishes an initial relationship among a creative question, relevant constraints, and criteria for examining possible results. Students might begin through observation, a material encounter, a provisional sketch, an annotated reference, or a spoken account of an emerging concern. The record should identify something to investigate rather than demand a fully resolved concept before making begins. Depending on the objective, AI may clarify unfamiliar terminology or generate questions that help locate a problem, but the student selects the direction to pursue. A brief checkpoint asks what the work is investigating and what evidence would indicate progress. This makes the initial intention available for later comparison without treating early commitment as an obligation to preserve a weak idea. The phase extends studio practices of envisioning and reflecting while responding to research on fixation by keeping alternatives open (Hetland et al., 2013; Wadinambiarachchi et al., 2024). A revised intention is therefore evidence of inquiry when the change can be explained, not a failure of planning.

Bounded assistance translates the task allocation into an interaction that makes the retained student decision explicit. Rather than requesting a completed solution, a student might request two explanations of a formal principle, questions about an existing composition, or contrasting possibilities that preserve a stated constraint. The request should make clear what AI may contribute and what remains to be decided through observation or testing. An educator can initially model this distinction through a shared example and then ask students to describe how assistance will advance the current objective. The model draws on evidence that purpose-designed tutoring can support learning, while avoiding the assumption that a prompt alone guarantees appropriate behavior (Kestin et al., 2025). A response that supplies the protected decision becomes material for diagnosis rather than an automatic replacement for student work. Students can reject the response, request narrower assistance, or return to a teacher, peer, or approved reference. The checkpoint concerns the educational function of assistance, not the complexity or length of the prompt.

3.4 Comparison of Alternatives and Purposeful Revision

Comparison converts available alternatives into an occasion for disciplinary judgment. Students examine a manageable selection of generated, self-produced, observed, or researched possibilities against the criteria established through intention formation. In an introductory task, the comparison might isolate balance, contrast, proportion, or a relationship between material and effect. In a more advanced task, it might address a tension among conceptual coherence, cultural interpretation, accessibility, and practical constraints. The important evidence is a reasoned account of a consequential difference, including why an apparently polished alternative may not serve the intended purpose. This requirement responds to findings that generated possibilities can improve an individual product while narrowing exploration across outputs (Doshi & Hauser, 2024). It also builds on formal-analysis pedagogy by making visual description and interpretive reasoning part of the production process (Carpino & Hutson, 2024). A brief annotated comparison can therefore provide more useful learning evidence than an extensive collection of unexamined alternatives.

Purposeful revision requires a decision about what should change, what should remain, and how that choice follows from the comparison. Students may revise through drawing, construction,

material experimentation, digital manipulation, a constrained generation request, or a combination of methods appropriate to the objective. The student first identifies the intended effect of an intervention and then examines whether the result supports that prediction. This separates purposeful iteration from repeated generation in search of an attractive outcome. The phase connects constructive engagement with the iterative processes described in art-education research (Chi & Wylie, 2014; Hutson & Cotroneo, 2023). It also recognizes the ownership relevance of opportunities to influence an outcome, without making the number of edits a proxy for creative agency (Pennanen et al., 2026). A defensible decision to retain an element can satisfy the phase when comparison supports that choice. The essential evidence is an explained relationship among intention, intervention, and observed consequence, rather than visible change for the sake of proving human involvement.

3.5 Human Critique, Reflection, and Independent Transfer

Human critique tests the relationship between intended meaning and interpretation beyond the immediate production dialogue. Peers and educators examine the work using shared disciplinary criteria while remaining open to alternative interpretations. Students explain a consequential decision, consider a challenge, and decide whether the challenge warrants revision, further investigation, or a reasoned defense. AI-generated feedback can serve as an additional perspective, but it does not replace the interpersonal exchange through which interpretations become contestable. The educational value lies in evaluating and acting on feedback rather than simply receiving comments (Nicol & Macfarlane-Dick, 2006). This phase also supports interactive engagement when discussion produces reasoning that extends beyond an initial explanation (Chi & Wylie, 2014). A concise record can capture one critique point and the resulting response, avoiding a transcript of every exchange. The checkpoint asks whether the student can connect a response to disciplinary evidence and an evolving creative purpose.

Reflection with independent transfer distinguishes an account of participation from evidence of a developing capability. Students identify a consequential decision, explain the role of assistance, and specify something now understood or performed more effectively. A related task then changes one relevant constraint and asks for the target reasoning without AI supplying that reasoning. The transfer task might require a fresh compositional adjustment, an explanation of an unfamiliar example, or a justified material choice under changed conditions. Access supports and alternative response modes remain available when these do not perform the assessed judgment (CAST, 2024). A delayed check can supplement the immediate task when durable learning is central to the objective (Soderstrom & Bjork, 2015). Separate, non-graded reflection can ask whether the process felt self-directed and whether the artifact felt personally representative, drawing attention to ownership without treating sentiment as achievement. The final checkpoint therefore integrates demonstrated learning with an account of collaboration while preserving the distinction between the two.

4. Applications in Secondary and Postsecondary Art and Design

4.1 Secondary Courses: Structured Inquiry and Visible Decisions

In secondary art and design courses, the model can begin with a limited set of formal relationships and a transparent explanation of why particular decisions remain with students. For an assignment addressing visual hierarchy, the objective might require students to predict and explain how contrast, scale, and placement organize attention. Protected activity would include an initial compositional study and an explanation of the intended emphasis. Supported activity could include terminology clarification, comparison questions, or teacher-selected generated examples that contain productive strengths and errors. A peripheral operation such as organizing comparison images could be delegated when checking the result does not require the very knowledge under assessment. Students would then compare alternatives, revise or defend a consequential choice, and discuss interpretation through a short critique. A new arrangement or changed emphasis would provide the transfer task, with annotation, speech, or demonstration available as response modes. This application connects formal-analysis instruction with graduated support and an accessible route to disciplinary explanation (Carpino & Hutson, 2024; CAST, 2024).

A second secondary application can center on material investigation rather than image production. Students examine how surface, structure, or spatial arrangement affects an intended expressive or functional outcome. AI can supply questions or tentative possibilities for investigation, but the relevant material behavior must be examined through direct handling, observation, or an appropriate accessible equivalent. The protected activity is the relationship between a prediction and the evidence obtained from a test. A comparison can include a generated representation precisely because representation may diverge from the behavior of the actual material. Students then explain which aspects of an initial proposal survived testing and which required revision. This prevents visual plausibility from substituting for technical or embodied understanding, addressing the ideation-execution gap identified in higher art-education research (Fang, 2026). The sequence remains suitable for beginning learners because the scope of the decision can be modest even when the underlying habit of inquiry is demanding.

4.2 Postsecondary Courses: Negotiated Delegation and Complex Judgment

In postsecondary art and design courses, the same model can accommodate more ambiguous briefs and competing criteria without assuming that all foundational capabilities are already secure. Students can propose a division of activity that identifies the conceptual, formal, technical, and interpretive decisions central to the project. An educator reviews this proposal against course outcomes and evidence of relevant experience. A student may delegate incidental production while retaining responsibility for the development of a concept, evaluation of alternatives, and response to cultural or material constraints. When an objective concerns a

new technique or unfamiliar form of interpretation, protected practice remains appropriate despite advanced course standing. Supported inquiry can include counterexamples, explanations, or alternative approaches that must be checked through sources, observation, and critique. The final defense should address why the chosen process was suitable for the objective and how the resulting artifact responds to the brief. Such an arrangement extends outcome-based AI permissions through a more detailed account of where disciplinary judgment resides (Hutson, 2025a; Perkins et al., 2024).

Progression across course levels therefore concerns the complexity of the retained decision and the degree of justified independence, not a predetermined increase in AI-generated content. An introductory student might compare two clear alternatives, whereas an advanced student might evaluate conflicting interpretations across several constraints. An advanced project may also require a return to direct material experimentation when generated representations cannot establish feasibility or meaning. Educators can increase the scope of delegation only when a student can specify acceptable outputs, identify consequential errors, and explain the effect of corrections. The same rule allows intensive support for a new domain while recognizing expertise already demonstrated elsewhere. A brief allocation review at a major transition keeps the process adaptable without imposing constant approval requirements. This emphasis aligns with research identifying critical judgment and teaching context as central to design-education integration (Fleischmann, 2026). It also keeps the purpose of secondary and postsecondary coursework visible: the development of creative capability rather than the accumulation of technically impressive outputs.

4.3 Assessment of Creative Process and Demonstrated Learning

Assessment in the framework combines the artifact, a selective record of consequential decisions, and an independent check of the targeted capability. A compact process portfolio can include a provisional intention, one annotated comparison, one revision or retention decision, and a response to critique. These items are selected because each supports an inference about disciplinary reasoning, not because documentation volume establishes effort. The final artifact remains important as evidence of communication, coherence, and execution within the stated brief. However, a strong artifact does not compensate for an inability to explain a target decision when that explanation is an explicit learning outcome. Equally, a productive failure can demonstrate learning when the student identifies the underlying problem and adapts the approach. Table 2 connects assessment criteria to evidence and instructional follow-up. This combination applies constructive alignment while responding to research showing that assisted product improvement and knowledge development need not coincide (Biggs, 1996; Fan et al., 2025).

Table 2. Assessment Criteria and Diagnostic Follow-Up

Criterion	Evidence sought	When further instruction is needed
Disciplinary reasoning	Explain a consequential decision through relevant formal, technical, material, or interpretive criteria.	The explanation relies on preference or generated language without connecting a choice to observable evidence.
Evaluation and revision	Compare alternatives, predict a change, and justify an intervention or a decision to retain an element.	Repeated generation replaces comparison, or changes cannot be related to an intended effect.

Independent transfer	Adapt the target capability to a changed example, brief, material, or constraint without generative substitution.	A successful artifact is not accompanied by a workable explanation or performance under the new condition.
Artifact communication	Demonstrate coherence, purposeful execution, and an appropriate response to the stated brief.	Visual polish obscures unresolved conceptual, material, contextual, or communicative problems.

Independent transfer checks should be narrow enough to isolate the intended capability and authentic enough to retain disciplinary meaning. A changed scale, context, material, audience, or formal constraint can require adaptation without demanding a second complete project. The educator specifies which reasoning must be performed without generative substitution while retaining access tools and other supports unrelated to that reasoning. A brief live explanation can be paired with annotated work when verbal fluency alone would provide an incomplete picture. Process records also require interpretation because generated explanations can imitate reflective language without demonstrating the associated understanding. For this reason, documentation should be considered alongside observed decisions and performance under a new condition. The criterion is convergence across evidence sources rather than confidence in any single record. When the sources disagree, the immediate response is diagnostic instruction and another opportunity to demonstrate understanding, consistent with formative rather than solely punitive assessment (Nicol & Macfarlane-Dick, 2006; Soderstrom & Bjork, 2015).

Reflection on ownership serves a different purpose from assessment of achievement. Students can describe how much influence was experienced over the process, which contributions felt consequential, and whether the artifact represented an intended identity or meaning. These accounts can reveal discomfort with a mode of assistance even when the submitted work is strong. Conversely, a student may feel considerable ownership while needing further instruction in a particular technique or interpretive practice. Keeping the two forms of evidence separate follows the distinction between authorship declaration, psychological ownership, and influence identified in human-AI research (Draxler et al., 2024; Pennanen et al., 2026). Ownership responses should therefore support discussion and research rather than reward enthusiastic adoption or penalize ambivalence. A brief contribution statement can identify the functions performed by AI and the decisions retained by the student. Neither that statement nor a positive ownership response should be treated as a determination of legal rights; the instructional purpose is to articulate participation and responsibility.

5. Discussion

5.1 From AI Permission to the Design of Learning

The framework shifts AI integration from a general question of permission toward a specific account of the activity through which learning should occur. Existing research already demonstrates that outcomes depend on interaction design, opportunities for influence, and the distinction between supported performance and later capability (Darvishi et al., 2024; Kestin et al., 2025; Pennanen et al., 2026). The model translates those findings into a recurring decision about whether assistance protects, supports, or replaces the intended learning function. The practical contribution is the connection among allocation, recursive production, critique, and transfer evidence. This connection also clarifies why the same operation may receive different treatment across assignments.

Generating a complete composition may replace learning when composition is the target, yet generated examples may be appropriate when critical comparison is the target. Likewise, direct fabrication remains essential when material technique is central, while automation of a peripheral production step may create more time for conceptual inquiry. Educational value therefore depends on alignment between the division of activity and the intended capability, not on an assumed opposition between human making and computational assistance.

5.2 Teacher Mediation, Access, and Sustainable Implementation

Implementation requires a manageable routine that makes retained decisions visible without turning studio practice into continuous reporting. Educators can introduce the model within one existing assignment and use two short checkpoints: one before major generation and another before final submission. The first checkpoint reviews intention and proposed assistance, while the second examines a consequential comparison or revision and readiness for transfer. The appendix provides a reusable planner that condenses these decisions into a single assignment-design instrument. Shared examples, small-group critique, and brief oral or visual explanations can distribute feedback while maintaining attention to disciplinary reasoning. Research on design education makes technical and pedagogical support relevant to this implementation work, although associations with reported outcomes should not be mistaken for causal evidence about a particular routine (Zhang, 2026). The framework consequently positions teacher expertise in task design and interpretation of evidence, not in monitoring every interaction. Documentation remains proportional to the decisions that matter for learning.

Accessible implementation also requires a distinction between removing generative substitution and removing support. Alternative formats, speech input, captions, adaptive interfaces, and accessible materials can remain available when the target judgment is still performed by the learner (CAST, 2024). An equivalent route using teacher-prepared examples or non-AI resources should preserve the learning objective when direct tool access is unavailable or inappropriate. Tool selection and account arrangements should follow institutional safeguards, with attention to privacy, age-appropriate access, and unnecessary exposure of personal or unpublished work (Miao & Holmes, 2023). Students should also examine how generated representations encode omissions, stereotyped assumptions, or culturally superficial associations, using disciplinary sources and human discussion to evaluate these issues. International competency guidance supports integrating ethical judgment with technical understanding rather than reducing AI literacy to effective prompting (Miao et al., 2024). These requirements are part of task design because resource access and representational choices shape the conditions under which participation occurs. A process-centered curriculum therefore treats equity, critique, and access as continuing features of creative inquiry rather than end-of-project declarations.

5.3 Research Implications

The framework yields testable questions about how the allocation of creative decisions relates to learning, exploration, and ownership. Comparative classroom studies can examine the proposed model against otherwise similar assignments with general AI permission or conventional instruction, using equivalent briefs, teaching time, and access conditions. Baseline measures should establish domain experience and the targeted capability rather than rely on course level as a proxy. Outcomes can include blinded evaluation of artifacts, quality of disciplinary explanations, immediate and delayed transfer, and diversity across a collection of work. Process ownership and product ownership should be examined separately through carefully developed measures and interviews, with attention to whether the dimensions are empirically distinguishable. A central hypothesis is that retaining consequential decisions will predict stronger independent reasoning even when the amount of generated content is substantial. A second hypothesis concerns whether structured comparison reduces fixation without diminishing purposeful autonomy, extending questions raised by visual-ideation and process-scaffolding research (Wadinambiarachchi et al., 2024; Wen et al., 2026).

Secondary and postsecondary studies can investigate how prior experience, task type, access conditions, and instructional support alter these relationships, producing evidence for refining the model at the level of actual classroom practice.

6. Conclusion

Generative AI creates an educational challenge when the production of an accomplished artifact becomes detached from the learning that the assignment is intended to develop. Research in learning, creative performance, authorship, and art and design education provides a consistent reason to examine the organization of assistance rather than treat access as inherently beneficial or harmful. The Process-Centered AI Integration Framework responds by allocating tasks through protect, support, and delegate modes and connecting those modes to six recursive phases of creative work. Retained decisions, bounded assistance, annotated comparisons, purposeful revision, human critique, and independent transfer make the relationship between process and learning explicit. The model also separates perceived ownership from demonstrated achievement, allowing creative identity and participation to remain meaningful without becoming proxies for competence. Across secondary and postsecondary courses, the degree of assistance follows the learning objective and the capacity to evaluate an output. This approach preserves material inquiry, disciplinary judgment, and creative experimentation while making space for useful automation. The resulting instructional priority is not to minimize AI, but to ensure that assistance strengthens the conditions for learning rather than replacing the learner within those conditions.

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Appendix A

Table 3. Process-Centered Assignment Planner

Design decision	Record for the assignment
Learning objective	Identify the formal, technical, material, or interpretive capability to be demonstrated; specify what a successful explanation or performance would show.
Protect	Name the decision or action students must perform directly because it is the target of learning or assessment.
Support	Identify explanations, questions, examples, feedback, or access tools that help without supplying the protected decision.
Delegate	Identify peripheral operations; explain how students will specify acceptable outputs, verify results, and correct consequential errors.
Intention and comparison	Select a brief initial record and an annotated comparison that make the creative question and evaluation criteria visible.
Revision and critique	Specify one consequential intervention or retention decision and one response to human critique.
Transfer check	Change a relevant constraint and require the target reasoning without generative substitution; retain appropriate accommodations.
Access and workload	Provide an equivalent participation route, confirm appropriate tool access, and limit documentation to evidence relevant to the objective.
Ownership reflection	Invite separate, non-graded reflection on influence over the process and connection to the artifact; do not equate either with learning.