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Reimagining Art Education: Teaching Drawing and Painting in the Age of Artificial Intelligence

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Abstract

The advent of generative AI applications such as DALL·E, Midjourney, and Stable Diffusion is impacting the pedagogy, practice, and evaluation of drawing and painting. While these tools open new possibilities for ideation, prototype testing, and individualized feedback, they also pose challenges to pedagogical values that traditionally focused on observation, embodiment, and intentional craftsmanship. This study explores the gap created by the lack of a coherent, evidence-based pedagogical framework for incorporating AI in teaching drawing and painting. A hybrid methodology framework is utilized that combines systematic review, guided by Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) (Page et al., 2021a), and Design Science Research (DSR). PRISMA informs a systematic review of recent literature, while DSR guides the development and evaluation of an artifact—a novel concept that emerges from this literature synthesis. The AI-Augmented Drawing and Painting Pedagogy (AADPP) model includes four intertwined components: foundational craft, AI-assisted ideation, critical and ethical reflection, and reflective studio practice. These concepts are built upon principles of constructivism, Technological Pedagogical Content Knowledge (TPACK), and AI literacy. The AADPP concept is evaluated through a six-criterion face validation, comparative analysis against similar studies, and a descriptive case study illustrating its implementation within a 12-week foundation drawing studio. The evaluation indicates that the proposed model is conceptually sound (complete, applicable, and current); this is illustrated by a detailed example of applying the model within a 12-week foundation drawing course. The current study does not include new empirical data; however, the case-study description serves as one means of evaluation. Limitations and directions for future empirical work are provided.

Keywords

Artificial Intelligence, Art Education, Drawing and Painting Pedagogy, Generative AI, PRISMA, Design Science Research

1. Introduction

Throughout history, art education has evolved alongside new technologies: from nineteenth-century photography to contemporary digital painting software. The latest disruption in arts education comes from generative artificial intelligence (AI), which refers to text-to-image AI that can create realistic visual artworks from language input, thereby condensing some steps of the creative process that previously required long-term training (Dehouche & Dehouche, 2023; Zhang et al., 2025). Scholarly interest towards AI's integration in arts education increased drastically in 2023-2025. Text-to-image generation and conversational AI gained popularity as topics in classes on composition, illustration, prompt design, and cultural heritage (Jiang, 2026; Rong et al., 2025). Educators and learners share a contradictory attitude towards generative AI's influence on visual arts education: while it stimulates creative thinking, supports less technically proficient learners, and makes creative processes accessible to everyone, fears arise concerning the loss of authorship, homogenization of style, as well as diminishing basic observation and material skills (Desdevises, 2025; Heaton et al., 2024; Wang et al., 2025).

This issue is particularly pertinent in drawing and painting: the relationship among one's hand, eye, and materials has been recognized as a cornerstone of any artwork (Hall & Schofield, 2025; Hu & Li, 2025; Ogunleye et al., 2024). Drawing is not about making marks but a specific way of looking at something, a skill that shapes one's vision and helps develop critical material judgement (Edwards, 2012; Wolk et al., 2020). Painting extends this practice by exploring colour, surface, and temporality. With the help of AI tools, it becomes possible to produce an elaborate drawing or a painting based on text input. This leads us to the pressing pedagogical question: what would the instruction of drawing and painting look like with the involvement of AI technologies?

Recent empirical studies show that AI tools, if integrated into an educational framework, increase learners' engagement, self-efficacy, and their creative output (Bian et al., 2025; Rong et al., 2025). Still, there is no empirically supported pedagogical model that addresses AI's integration in drawing and painting and shows how this can be done without displacing basic learning experiences of aspiring artists. Research in this field is scattered across disciplines, contexts, and tools (Hutson & Cotroneo, 2023a; Jiang, 2026; Lee & Palmer, 2025;). There is a need for a comprehensive, theory-informed model that combines AI literacy, studio practice, and reflection on ethical issues arising with the integration of AI in arts education (Jiang et al., 2026; Lee & Palmer, 2025).

This study aims to address the identified gap. It investigates three research questions: (RQ1) What are the current uses, benefits, and limitations of AI in the instruction of drawing and painting? (RQ2) How can we design a pedagogical model of integration of AI in the instruction of drawing and painting? (RQ3) To what extent can this model be judged conceptually sound (complete, applicable, relevant, clear, general, and current) through face validation, comparative analysis, and an illustrative case study? For this purpose, the research employs PRISMA + DSR methodology inspired by successful design-science research (Al-Dhaqm et al., 2017a, 2020; Al-Mugern et al., 2024). The contribution of this research is a theory-informed, conceptually developed AI-Augmented Drawing and Painting Pedagogy (AADPP) model, along with its evaluation and application.

The rest of the paper is organized as follows. Section 2 covers the literature review. Section 3 describes the methodology. Section 4 presents the AADPP model itself. Section 5 deals with its evaluation. Section 6 offers an example case study of AADPP. Section 7 compares the model with relevant studies. Section 8 discusses the results of the study. Limitations of the project and plans for future empirical research are discussed in Section 9. Section 10 concludes the manuscript.

2. Related Works

2.1. Generative AI Tools in Visual Art Education

The current wave of text-to-image generators deployed in the field of education are based on the principles of diffusion models, commonly combined with transformer architectures implementing a denoising mechanism, with previous GAN approaches relegated to the role of supporting mechanisms (Goodfellow et al., 2020; Po et al., 2024). In turn, the main consumer-grade systems-DALL·E, Midjourney, and Stable Diffusion-are built according to these principles (Adetayo, 2024; Hutson & Cotroneo, 2023b). These systems increasingly incorporate advanced multimodal user interfaces enabling not only text-to-image generation but also conditions of image-to-image, in-painting capabilities, and structural prompts implemented via ControlNet, which allows generating images constrained with the help of a student's line drawing, edge maps, depth maps, or pose references (Zhang et al., 2023). This aspect has significant pedagogical implications as it means that there is an overlap between the processes of observational drawing and generative AI, and thus, the framing of the phenomenon of AI in education limited to prompt-only systems misses a critical point.

From the perspective of systematic literature reviews, the fields of creative production, scaffolded instruction, and content generation emerge as key areas of applications for generative AI in art education from 2019 to 2025 (Jiang et al., 2026; Rong et al., 2025). According to empirical studies, the introduction of AI generated images in conjunction with teacher-mediated fine-tuning leads to greater student engagement, increased self-efficacy, and heightened levels of satisfaction (Bian et al., 2025). Empirical research in the context of training in graphical and abstract arts indicates that students need to possess certain visual literacy and design skills to transform the results produced by generative AI into meaningful art pieces (Chiu & Hwang, 2025; Hiçyılmaz, 2025; Hwang & Wu, 2025). The question of whether prompt engineering will remain an important independent skill seems debatable as multimodal interfaces increasingly support not only text but also conversation and images; thus, the key unit of student work shifts from prompts to workflow.

According to empirical studies on AI-assisted painting courses, students' intent to continue the experience is driven by the perceived usefulness and ease of use of these technologies, combined with teacher mediation, which validates classic TAM predictions in this creative domain (Li et al., 2026; Sun et al., 2025). Systematic reviews of AI in child education highlight concerns about the potential for cognitive standardization inherent in these AI-driven interfaces (Wang et al., 2025). Comparative studies that focus on different models (Midjourney, Stable Diffusion, DALL·E) applied to design education reveal the impact of model choice on the resulting cognitive and creative profile of student work (Adetayo, 2024; Derevyanko & Zalevska, 2023).

2.2. Foundational Drawing and Painting Pedagogy

The literature on observational drawing pedagogy long predates generative AI and is essential context for any AI-integrated model. Edwards's widely used pedagogy reframes drawing as a perceptual rather than a mechanical task, organized around five perceptual skills: edges, spaces, relationships, lights and shadows, and the gestalt of the whole (Edwards, 2012). Empirical studies of drawing-from-observation report measurable effects on visual attention, emotional regulation, and self-perception among adolescents (Wolk et al., 2020). Foundational studio sequences typically progress from blind-contour and gesture drawing, through tonal value studies, to colour mixing and material handling in media such as charcoal, ink, watercolour, and oil (Hu & Li, 2025). Recent transfer-effect studies in museum settings demonstrate that even short, structured drawing programmes can produce measurable socio-emotional gains (Kastner et al., 2021). Studies of digital drawing software show that affordances such as layer control and unlimited undo can support specific artistic skills but do not automatically substitute for material judgement built in analogue practice (Hu & Li, 2025). Any AI integration must engage seriously with this pedagogical inheritance rather than treat AI as a self-sufficient teacher of drawing.

2.3. Pedagogical Theories Underpinning AI Integration

Three theoretical frames recur in the literature. First, constructivist and socio-cultural learning theory, especially Vygotsky's zone of proximal development and scaffolding, frames AI tools as potential more-knowledgeable others that can support learners between current and potential performance (Malik, 2017). Second, the Technological Pedagogical Content Knowledge (TPACK) framework specifies the intertwined knowledge bases that teachers need to integrate technology thoughtfully into subject-specific pedagogy (Koehler et al., 2013; Mishra & Koehler, 2006). Third, the Technology Acceptance Model (TAM) (Davis, 1989) and its educational extensions remain widely used to explain learners' intention to use AI tools, including in design and painting studios (Granström & Oppi, 2025; Sun et al., 2025).

Alongside these frames, AI literacy frameworks have crystallized around Long and Magerko's competencies for recognizing, evaluating, and ethically using AI (Long & Magerko, 2020), extended by global guidance from UNESCO and the OECD that emphasize human-centred, ethical, and inclusive deployment (Miao & Holmes, 2024; OECD, 2023). Recent competency syntheses confirm that AI literacy must combine technical, evaluative, practical, and ethical dimensions across school and higher-education learners (Chee et al., 2025).

2.4. Ethics, Authorship, Training Data, and the Value of Human Practice

Legal and ethical considerations related to the use of AI-generated art include issues of authorship, the origin of training data, and the replacement of human creativity (Jung & Yoon, 2025; Singh, 2025). Legal-philosophical analysis further examines the possibility of copyright protection for AI-generated content, arguing that generative AI outputs lack the characteristics of human authorship, making the use of such models in students' artworks an issue for grading, citation, and presentation. In terms of art education, the discussion prompts educators to ask several important questions, namely about the origin of training data, the potential impact of "in the style of" on living artists, and the information that must be disclosed to audiences.

The scholarly literature suggests that AI-generated art could be considered a form of collaboration or cocreation, in which the role of the person involved shifts from that of a single creator to that of a curator, prompter, and concept designer (Sáez-Velasco et al., 2024; Zhou & Lee, 2024). Studies on human-AI cocreation show that although AI may demonstrate equivalent or even superior performance to humans on creativity measures, domain experts still identify shortcomings in the originality and contextuality of AI-generated works (Acar et al., 2025; Guzik et al., 2023). Art educators have called for an integrative approach to using AI in the classroom that combines classical teaching methods with AI reflection (Heaton et al., 2024; Heaton, 2025).

2.5. Methodological Precedents: PRISMA and DSR

PRISMA 2020 defines a clear framework for systematic reviews through a checklist of 27 items and modified flow diagrams (Page et al., 2021a, 2021b). Design Science Research (DSR), as defined in the field of information systems by Hevner et al. and Peffers et al., offers a complementary approach in which the researcher continuously designs, develops, and evaluates artifacts to resolve real-world problems (Hevner et al., 2004; Hevner, 2007; Peffers et al., 2007). The combination of a PRISMA-guided systematic review with DSR-based artifact construction and multi-method validation is well established in adjacent technical domains, most notably digital forensics, where Al-Dhaqm and colleagues developed and face-validated process models and meta-models spanning common investigation processes, their categorization, and cloud-based data collection (Al-Dhaqm et al., 2017a, 2017b, 2020, 2021a, 2021b; Al-Mugern et al., 2024). To the best of our knowledge, however, this combined approach has not previously been applied to drawing-and-painting pedagogy. The present study therefore transfers an established methodological template from a technical domain to a humanistic, studio-based one, pairing a systematic review with artifact design and multi-method validation.

3. Methodology (PRISMA + DSR)

This research uses PRISMA 2020 as the structure for conducting systematic literature reviews and incorporates a Design Science Research (DSR) methodology to develop, evaluate, and analyze the proposed pedagogy framework. The role of using both frameworks is two-fold, including summarizing the knowledge base and developing what has not yet been designed.

3.1. PRISMA Phase

Following PRISMA 2020 guidance (Page et al., 2021a, 2021b), a systematic search was conducted across Web of Science, Scopus, ScienceDirect, IEEE Xplore, ACM Digital Library, ERIC, and Google Scholar. Search terms combined art-education vocabulary ("art education", "drawing", "painting", "visual arts curriculum", "studio practice"), AI vocabulary ("artificial intelligence", "generative AI", "text-to-image", "DALL·E", "Midjourney", "Stable Diffusion"), and pedagogy vocabulary ("pedagogy", "curriculum", "teaching model", "AI literacy"). The search window covered January 2019 to February 2026.

Table 1. Database search results across PRISMA phases.

Database	Identified	After duplicates	Screened (T/A)	Full text reviewed	Included
Web of Science	286	239	239	58	19
Scopus	312	241	241	61	22
ScienceDirect	174	147	147	33	11
IEEE Xplore	96	88	88	19	6
ACM Digital Library	103	88	88	21	7
ERIC	141	112	112	24	9
Google Scholar	135	98	98	15	5
Total	**1247**	**1013**	**1013**	**231**	**79**

Note. The synthesis was narrative-thematic, organized around uses, benefits, limitations, and pedagogical theories. The 79 included studies form the basis for thematic synthesis and the model design.

The inclusion criteria included: 1) peer-reviewed empirical studies, conceptual studies, or systematic reviews regarding the role of artificial intelligence (AI) in visual art education; 2) studies written in English; and 3) studies concerning drawing, painting, design, or related forms of visual art. The exclusion criteria included: studies examining only music or text generation; opinion studies without any empirical or conceptual basis; studies on AI in non-art forms of STEM where there is no potential applicability for visual arts. Screening was done first based on titles and abstracts, followed by full-text screening. The PRISMA flow diagram elements of identification, screening, eligibility, and inclusion are shown in Table 1 and Figure 1. The numbers provided in Table 1 are due to the structured searching process and the number of articles reviewed in model development. This study did not register its protocol with PROSPERO and hence no inter-rater reliability metrics are provided.

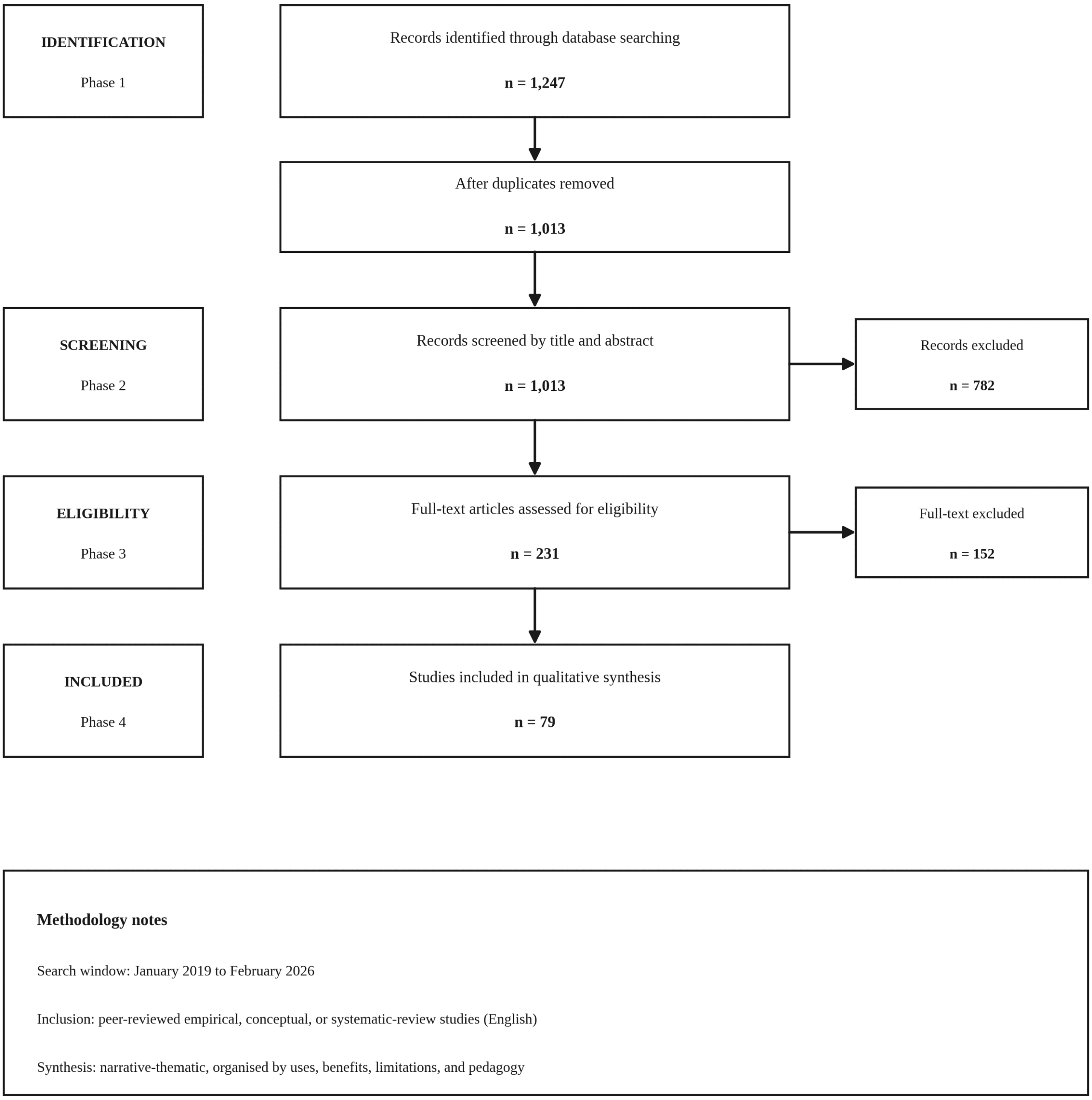

Figure 1. PRISMA 2020 flow diagram showing identification, screening, eligibility, and inclusion stages of the literature search.

3.2. DSR Phase

The DSR phase followed the six-activity Peffers et al. process model (Peffers et al., 2007) within the three cycles articulated by Hevner (Hevner, 2007). The relevance cycle drew problem requirements from the contemporary classroom—the need to teach foundational drawing and painting in a context where AI can produce polished images on demand. The rigor cycle anchored the design in constructivist learning theory, TPACK, AI literacy frameworks, observational-drawing pedagogy, and prior case-study work (Edwards, 2012; Long & Magerko, 2020; Malik, 2017; Mishra & Koehler, 2006; Wolk et al., 2020). The central design cycle iteratively developed the AADPP model through three internal iterations: an initial conceptual draft, refinement following literature synthesis, and refinement following expert review. The structure is depicted in **Figure 2**.

The six DSR activities were operationalized as follows:

Problem identification. Fragmented integration of AI in drawing and painting curricula; lack of a validated unifying model.

Objectives of a solution. To produce a model that integrates AI tools with foundational craft, ethical reflection, and AI literacy, applicable across foundation-level studio courses.

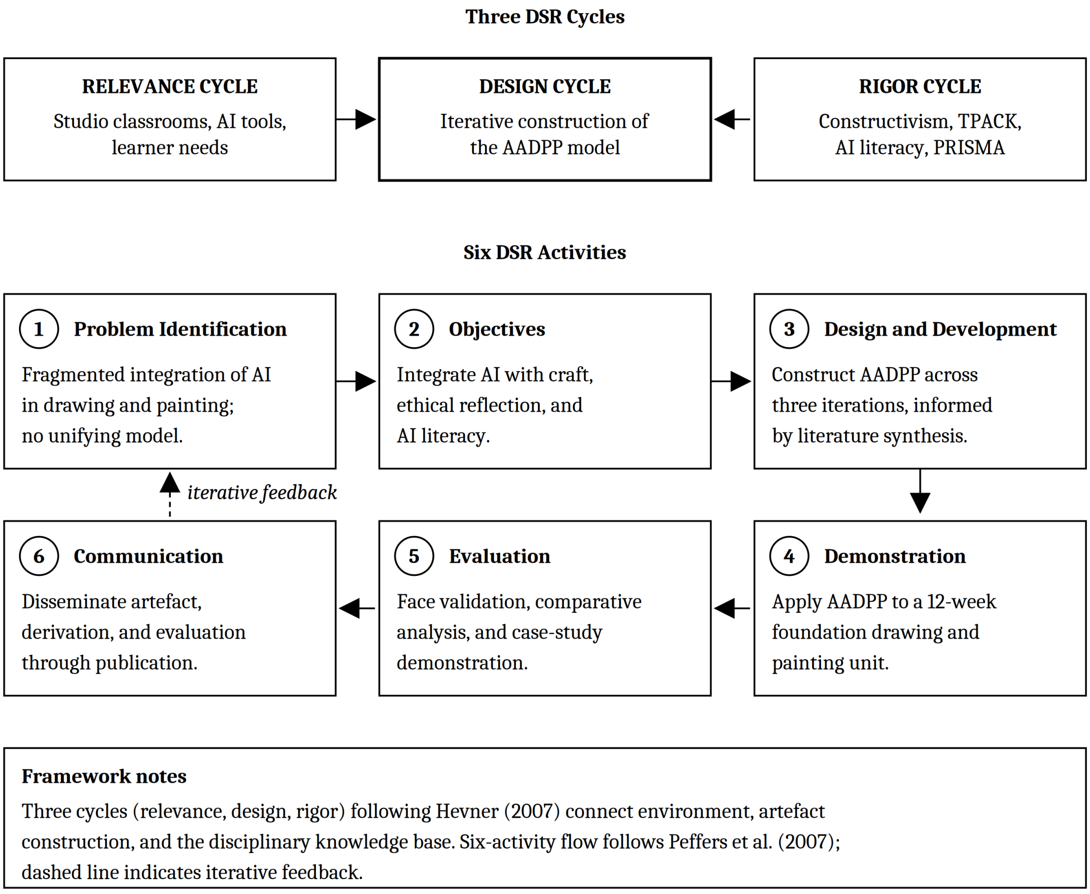

Figure 2. Design Science Research (DSR) comprises three cycles and six activities in the construction of the AADPP model.

Design and development. Construction of the AADPP model through three iterations, informed by PRISMA synthesis and prior models.

Demonstration. Application of the model to a foundation drawing and painting studio scenario over a 12-week unit.

Evaluation. Face validation by domain experts, comparative analysis with existing studies, and case-study observation.

Communication. The present paper communicates the artifact, its derivation, and its evaluation, following Peffers et al.'s template for design-science publications (Peffers et al., 2007).

3.3. Evaluation Methods

Three techniques have been utilized for evaluation:

1) Face validity based on criteria for completeness, applicability, relevance, clarity, generality, and currency by a panel of domain experts;

2) Comparative analysis with existing models and research works;

3) Illustration through a hypothetical case study.

Given that comprehensive empirical testing cannot be performed at the stage of the initial design-science research effort, these three evaluation techniques provide grounds for assessing the theoretical consistency and applicability of the proposed model, which remains to be tested empirically in the study described in Section 9.2.

3.4. From Synthesis to Artifact

The narrative-thematic synthesis of the included studies produced four recurring design requirements (DRs) that map directly onto the four layers of the AADPP model. DR1 (that foundational observation, mark-making, and material judgement are placed at risk when AI automates the early, formative stages of image production) is addressed by Layer 1, which protects analogue craft as a precondition for AI use (Edwards, 2012; Wolk et al., 2020; Wang et al., 2025). DR2 (that generative AI is most valuable for divergent ideation and exploration when the learner's own drawing remains in the loop through image-to-image and structural conditioning) is met by Layer 2 (Hutson & Cotroneo, 2023b; Zhang et al., 2023). DR3 (that responsible integration requires explicit attention to AI literacy, authorship, training-data provenance, bias, and equity of access) is met by Layer 3 (Long & Magerko, 2020; Miao & Holmes, 2024; Singh, 2025). DR4 (that assessment must reward process and craft rather than polished surfaces alone) is met by Layer 4 through a process journal and a craft-weighted rubric (Amabile, 1982; Heaton, 2025). Making this mapping explicit clarifies how each component of the artifact is grounded in the reviewed literature rather than asserted independently of it.

4. Proposed Model: AI-Augmented Drawing and Painting Pedagogy (AADPP)

The AADPP model is a four-layer pedagogical framework that situates AI as one component within a broader practice of learning to draw and paint. The four layers operate in an iterative, interactive manner rather than in a strict sequence. The structure is illustrated in Figure 3, and a layer-by-layer summary appears in Table 2.

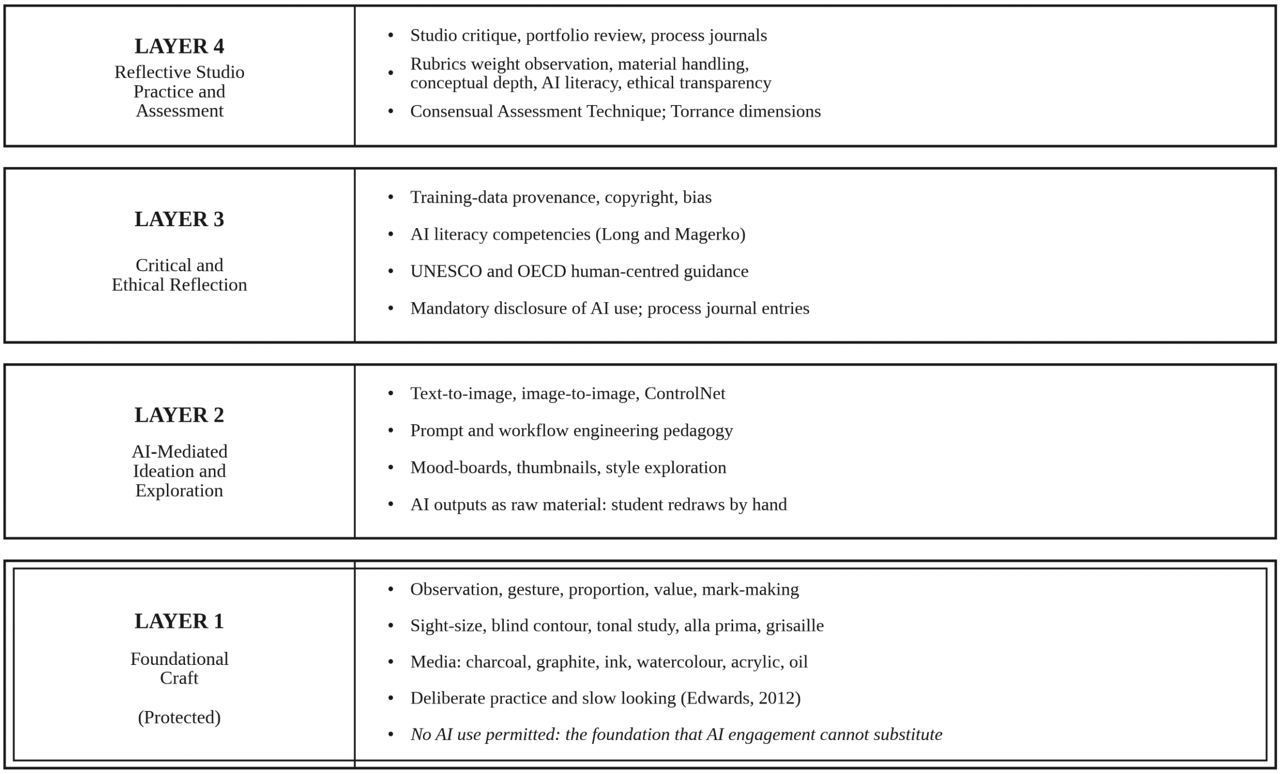

Figure 3. The AADPP four-layer model.

Table 2. AADPP model: layers, activities, tools, and assessment focus.

Layer	Primary aim	Activities	Tools/media	Assessment focus
L1. Foundational craft	Observation, mark-making, material judgement	Blind contour, gesture, sight-size, tonal studies, plein-air, alla prima, grisaille	Analogue media: charcoal, graphite, ink, watercolour, acrylic, oil	Observational accuracy; material handling
L2. AI-mediated ideation	Divergent ideation, exploration, structural prompting	Mood-boards, thumbnails, style exploration; image-to-image conditioning of sketches	Text-to-image and image-to-image: DALL·E, Midjourney, Stable Diffusion + ControlNet	Prompt and workflow design; iteration quality; translation to traditional media
L3. Critical & ethical reflection	AI literacy, authorship, training-data ethics, policy	Seminars on training data, copyright, style imitation; process journal; disclosure	Readings, case law, journal templates, policy texts (UNESCO, OECD)	Quality of reasoning; ethical transparency; AI literacy
L4. Reflective studio practice	Integration, critique, assessment of process and product	Studio critique, portfolio review, peer feedback, final painting	Rubrics, portfolios, journals; mixed traditional and digital outputs	Holistic rubric: craft, concept, AI literacy, ethics, process

4.1. Layer 1: Foundational Craft

Layer 1 protects and develops the embodied core of drawing and painting: observation, gesture, proportion, value, mark-making, edge control, colour mixing, surface, and material judgement. The layer draws on long-standing observational-drawing pedagogy that frames drawing not as the mechanical production of marks but as a perceptual discipline organized around edges, spaces, relationships, lights, and shadows, and the gestalt of the whole (Edwards, 2012). Activities are deliberately analog and include blind-contour and gesture drawing, sight-size cast and figure studies, tonal value studies in charcoal, plein-air painting, colour-temperature exercises, alla prima still-life, and underdrawings and grisaille methods for oil. Materials include charcoal, graphite, ink, watercolour, acrylic, and oil; acrylic is recommended as a starting medium in introductory courses where drying times for oil or studio infrastructure may be limited.

No AI tools are used in this layer. This restriction is based on experimental evidence regarding the effects of drawing from observation on visual perception, perceptual discrimination, and self-perception (Kastner et al., 2021; Wolk et al., 2020). Moreover, digital technology—especially generative AI—cannot replace the judgement of form obtained through analogue drawing. Automating the initial confrontation negates the very essence of learning that takes place through the cognitive and physical development that occurs when one draws. Such an approach supports Vygotsky's claim that the zone of proximal development needs to be actively developed by the learner, not bypassed (Malik, 2017).

4.2. Layer 2: AI-Mediated Ideation and Exploration

In this stage, AI image technologies serve as sketchpad helpers for ideation, mood boards, thumbnailing compositions, and quick experimentation with style and sources (Hutson & Cotroneo, 2023a, 2023b; Jiang, 2026). Two modes of operation can be outlined. First, the text-to-image mode, where students create, refine, and critique their prompts as design documents that show their ideas. Second, the image-to-image and structural conditioning (such as ControlNet) (Zhang et al., 2023) mode, where students feed their own sketches, line art, or pose references to the AI model to explore variation based on their own observation. The latter mode has greater educational value because the initial image remains within the process. In both modes, AI results are not perceived as end products but as source material to be redrawn and repainted into classical media (Hutson & Cotroneo, 2023a, 2023b).

4.3. Layer 3: Critical and Ethical Reflection

Layer 3 examines the social, ethical, and legal issues around AI in art, specifically around where training data comes from, copyright and attribution, the contentious legality of "in the style of" generations, bias and homogenization, and appreciation for human creativity (Jung & Yoon, 2025; Sáez-Velasco et al., 2024; Singh, 2025). Style imitation is of particular interest as a pedagogically relevant issue, as instructions to use a living artist's name can reproduce identifiable aspects of their work without permission or attribution, a practice currently under litigation in cases like Andersen v. Stability AI (Elmahjub, 2025). Cases like this will be analyzed by students in terms of policy and legislation and debated on when references to an artist's style can count as fair inspiration and when they become inappropriate appropriations, robbing an artist of their livelihood.

Equity and access issues are addressed in Layer 3. Choosing a specific AI tool is an ethical decision with different costs and implications depending on whether the tool is commercially available with a subscription model, freely available online but commercial, or is a free and open-source software solution such as Stable Diffusion running on one's own server (Miao & Holmes, 2024; OECD, 2023). Student options are discussed here, with an understanding of the consequences of each alternative. The layer meets the AI literacies outlined by Long and Magerko (Long & Magerko, 2020) and UNESCO's ethical and human-centered guidelines (Miao & Holmes, 2024) as well as current competencies (Chee et al., 2025). Students keep a process journal that tracks the choices made, including prompts and workflows used, AI-generated results referenced, accept/reject decisions, and the student's contribution. AI usage needs to be declared for every assessed piece, and its extent is clearly stated in the unit's assessment policy.

4.4. Layer 4: Reflective Studio Practice and Assessment

Layer 4 integrates work from the other three through studio critique, portfolio review, and process-oriented assessment. Building on the Consensual Assessment Technique and adapted Torrance dimensions of fluency, flexibility, originality, and elaboration (Amabile, 1982; Torrance, 1988), assessment evaluates both product and process. Rubrics give weight to observational accuracy, material handling, conceptual development, AI literacy demonstrated through the process journal, and ethical transparency. The layer is teacher-mediated and peer-supported, consistent with constructivist studio traditions and TPACK-informed integration (Koehler et al., 2013; Mishra & Koehler, 2006). The concrete rubric used to operationalize this layer is presented in Section 6.3.

4.5. Cross-Cutting Principles and Theoretical Foundations

Three principles cut across all four layers. First, human primacy: the human remains the author and decision-maker; AI is a tool (Miao & Holmes, 2024; Sáez-Velasco et al., 2024). Second, transparency: all AI use is disclosed and documented (Jung & Yoon, 2025). Third, iteration: the model is not linear; students move between layers across a project and across a program. **Figure 4** maps the model's theoretical foundations onto its expected learning outcomes.

Figure 5 grounds the model in actual studio outputs: a graphite gesture drawing, a charcoal tonal study, an AI thumbnail ideation grid with one variant selected, a finished hand-painted harbour scene, and a process journal page documenting AI use and ethical reflection.

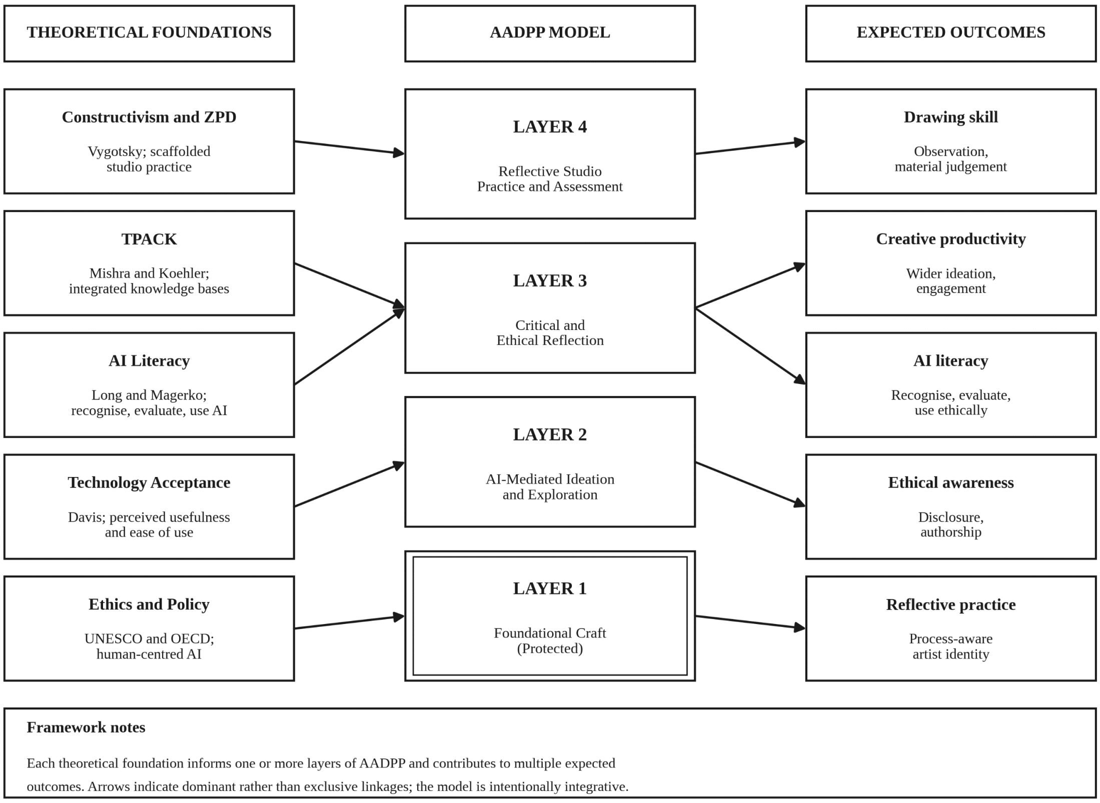

Figure 4. Theoretical foundations mapped to AADPP layers and expected learning outcomes.

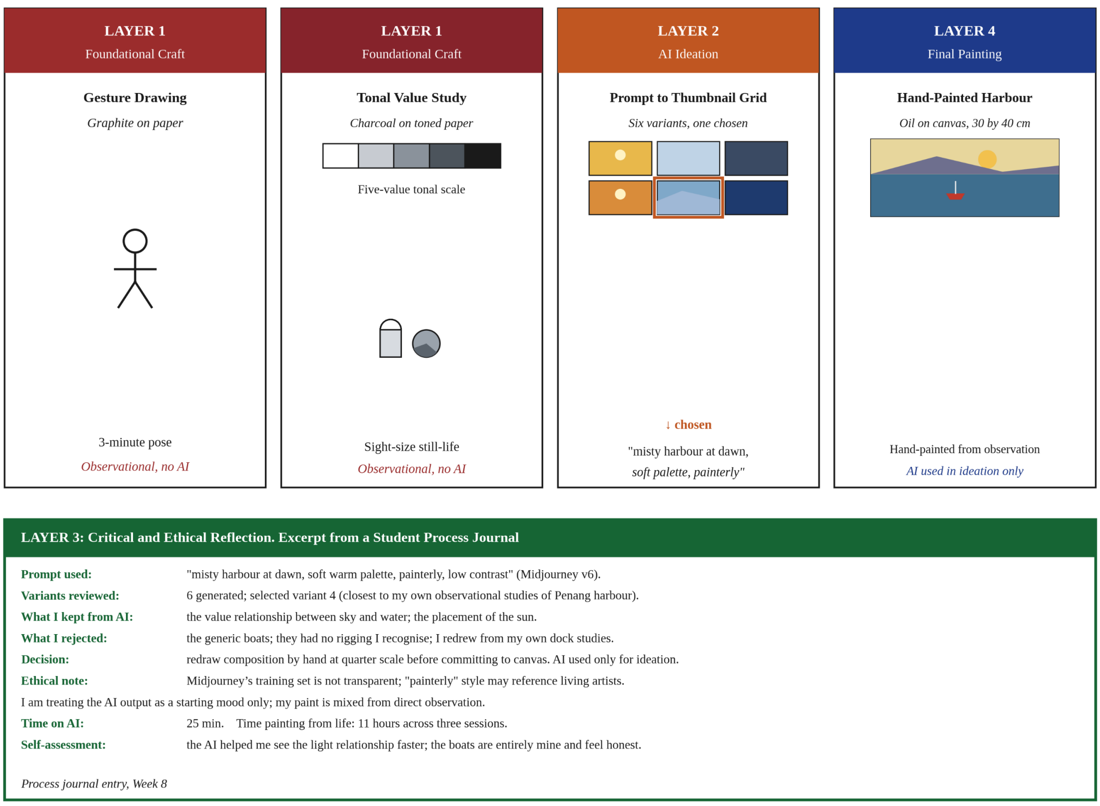

Figure 5. The four AADPP layers in practice.

5. Evaluation

The AADPP model was evaluated through face validation. Six criteria adapted from prior validation studies in conceptual modelling (Al-Dhaqm et al., 2017a, 2020, 2021a) were applied: completeness (does the model cover the relevant elements?), applicability (can it be applied in practice?), relevance (does it address the stated problem?), clarity (are concepts well-defined?), generality (can it be adapted across contexts?), and currency (does it reflect the current state of AI and art-education research?). **Table 3** summarizes the face validation. The face validation was carried out with a panel of five experts chosen to cover the model's principal knowledge domains: two studio drawing-and-painting instructors, one art-education researcher, one educational-technology specialist familiar with TPACK, and one specialist in AI ethics and AI literacy. Each expert received the model description, the layer definitions, and the accompanying figures, together with a structured instrument on which the six criteria were each rated as met, partially met, or not met, with space for open written comments. Their feedback fed directly into the final artifact: remarks on the dispersal of ethical content led to consolidating ethics and AI literacy into a standalone Layer 3; remarks on ideation led to making image-to-image and ControlNet-based structural conditioning explicit in Layer 2 so that the learner's own drawing remains in the loop; and remarks on assessment led to sharpening the Layer 4 rubric so that craft and process are weighted above polished AI output.

Table 3. Face validation of the AADPP model against six criteria.

Criterion	Definition	Evidence from the AADPP model	Result
Completeness	Does the model cover the relevant pedagogical elements identified in the literature?	Four layers align with dimensions in major reviews (Jiang et al., 2026; Rong et al., 2025): craft, ideation, ethics, assessment.	**Met**
Applicability	Can the model be applied in practice?	Maps to activities documented in empirical studies of AI-assisted drawing/painting (Bian et al., 2025; Hutson & Cotroneo, 2023a, 2023b).	**Met**
Relevance	Does the model address the stated problem?	Targets the integration of AI into drawing and painting, a gap repeatedly identified (Jiang et al., 2026; Lee & Palmer, 2025).	**Met**
Clarity	Are concepts and boundaries well-defined?	Each layer is defined by distinct activities, tools, and learning aims; cross-cutting principles named.	**Met**
Generality	Can the model be adapted across contexts?	Abstraction allows local adaptation; demonstrated for higher-education foundation studios. K-12 and community-arts adaptation outlined but not yet validated.	**Partially met**
Currency	Does the model reflect the current state of AI and art-education research?	Incorporates 2025-2026 sources on AI literacy, training-data law, and human-AI cocreation (Chee et al., 2025; Elmahjub, 2025; Miao & Holmes, 2024; OECD, 2023; Sáez-Velasco et al., 2024).	**Met**

Five of the six criteria are met outright. Generality is recorded as partially met because while the model's abstraction permits adaptation, only the higher-education foundation-studio scenario is worked out in detail in this paper; K-12 and community-arts adaptations are sketched in the limitations and earmarked for future design iterations.

Comparative analysis with recent systematic reviews of generative AI in art education indicates that the AADPP model unifies elements that previous proposals address in isolation. Existing studies focus on either prompt-engineering pedagogy (Hutson & Cotroneo, 2023a, 2023b), AI literacy (Chee et al., 2025; Long & Magerko, 2020), assessment of creativity (Amabile, 1982; Torrance, 1988), or ethical considerations (Jung & Yoon, 2025; Sáez-Velasco et al., 2024; Singh, 2025). The AADPP integrates these into a coherent four-layer artifact that preserves foundational craft as a protected layer rather than a residual concern.

6. Illustrative Case Study

This section outlines an example of a 12-week case study that illustrates how the AADPP approach can be applied within the context of an undergraduate program. The purpose of this case study is to provide a framework for demonstrating how the AADPP approach can be implemented without engaging in research, which involves collecting data from participants. This case study describes hypothetical results as patterns based on similar case studies (Bian et al., 2025; Hutson & Cotroneo, 2023a, 2023b) and the body of research regarding AI pedagogies in workshops (Hiçyılmaz, 2025).

6.1. Setting and Design

This scenario assumes a first-year studio class made up of about 24 students taking an introductory drawing and painting curriculum. This unit runs for 12 weeks and includes two three-hour studio sessions per week. Weeks 1 - 4 will run solely in Layer 1, where students learn observational drawing, sight-size and tonal value rendering, basic colour theory, and materials introduction. Acrylics are recommended for initial painting assignments, and oil painting will be introduced after that. During this period, the use of any AI tools is strictly forbidden to ensure the purity of the foundational skills being developed.

Layer 2 and 3 will start in Weeks 5 - 8. At this point, the students receive an introduction to prompt engineering and structuring/conditioning techniques (e.g., inserting their own contour drawings into image-to-image or ControlNet procedures) and then use the AI-assisted tools to generate ideation thumbnails for a self-conceived painting assignment. In this stage, AI outputs are considered part of the sketchbook, requiring the students to redraw critical elements by hand before creating a painting. Layer 3 will take place during weekly seminars on training data sources, copyright and style copying, bias issues, and recent legislation (e.g., Andersen v. Stability AI). Supplementing the lectures will be assigned readings from the AI literacy and regulation literature (Elmahjub, 2025; Jung & Yoon, 2025;

Long & Magerko, 2020; Miao & Holmes, 2024; Singh, 2025).

Weeks 9 - 12 include Layer 4. During this final phase, students will finish a painting assignment with a process journal listing all prompts and conditioning steps used, consulted AI outputs, acceptance/rejection outcomes, and reflections on craft and ethical considerations. Critiques will occur in groups, utilizing the rubric described in Section 6.3. The full week-by-week schedule for the unit is summarized in **Table 4**.

Table 4. Illustrative 12-week schedule applying the AADPP model in a foundation drawing and painting unit.

Week	Active layers	Activities	Deliverable
1	L1	Material introduction; blind contour; gesture drawing.	Sketchbook (analogue).
2	L1	Sight-size cast/object drawing; tonal value studies.	Tonal studies portfolio.
3	L1	Life drawing; proportion and gesture.	Life drawing sheets.
4	L1	Colour theory; plein-air or studio painting in acrylic.	Small acrylic studies.
5	L1 + L2 + L3	Introduce prompt-engineering and image-to-image; ethics seminar 1 (training data).	Prompt log; ideation mood-board.
6	L1 + L2 + L3	Compositional thumbnails (AI + hand); seminar 2 (style imitation, Andersen v. Stability AI).	Compositional thumbnails (mixed).
7	L1 + L2 + L3	Colour studies; style exploration; seminar 3 (authorship and disclosure).	Colour studies; reflection note.
8	L1 + L2 + L3	Final composition lock; redraw by hand; seminar 4 (bias, equity, open-source tools).	Final cartoon for painting.
9	L1 + L3 + L4	Underpainting (grisaille/burnt sienna); first peer critique.	Underpainting + critique notes.
10	L1 + L3 + L4	Mid-tone painting; refine process journal.	Painting in progress; journal.
11	L1 + L3 + L4	Detail and edge work; second peer critique.	Near-final painting.
12	L1 + L3 + L4	Final critique; portfolio submission with disclosure.	Final painting + journal + portfolio.

Figure 6 presents a case study in terms of time spent on one project from the prompt creation to the production of the final artwork, showing how the timing of the artwork is more determined by its drawing and painting components than

by the involvement of AI. In particular, the redraw step connecting the AI thumbnail sketch and the actual canvas plays an essential role, since it forces the artist to reproduce the AI picture based on personal observation.

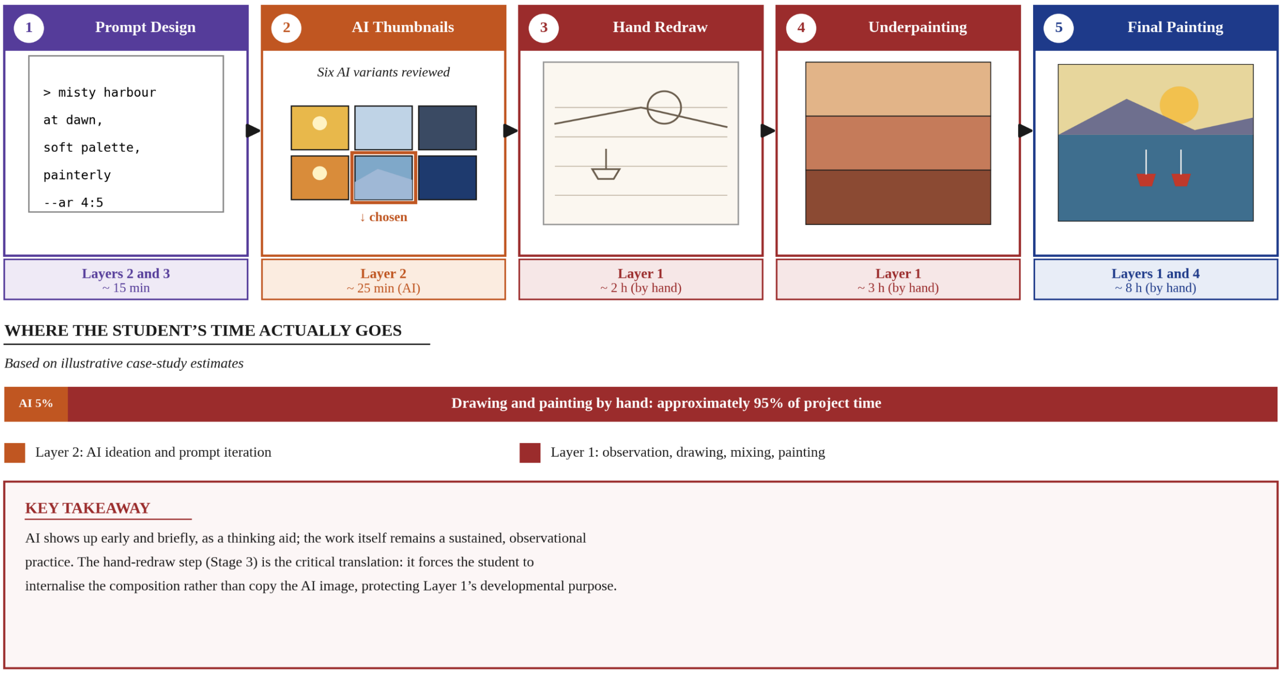

Figure 6. From prompt to painting: the AADPP workflow.

6.2. Example Prompts and Workflows

For Layer 2, an example of prompts and workflow for one project, "misty harbour at dawn", can be seen in Table 5 with varying degrees of AI engagement. This process is part of a specific teaching strategy where the students begin with prompts for broad texts, then move to structuring via drawing, and finally use AI-driven variations based on life drawing. The aim is not to replace life drawing but to support it.

Table 5. Example prompts and workflows across three levels of AI involvement (project: "misty harbour at dawn").

Level	Workflow	Example prompt/input
A. Broad text-to-image	Text prompt only; six variants generated, one selected for the mood-board.	"Misty harbour at dawn, soft warm palette, painterly, low contrast, early light on water, --ar 4:5"
B. Image-to-image/ControlNet	Student's own pencil thumbnail used as a structural condition (edge or depth map); AI fills in tonal and colour suggestions while preserving the student's composition.	Input: student's scanned pencil thumbnail. Prompt: "same composition, dawn light from upper-right, muted blue-grey water, fishing boats"
C. AI variation against life reference	Student paints from observation on location; AI used afterwards to generate alternative colour/light variants to inform a second painting.	Input: photograph of student's plein-air study. Prompt: "same scene, evening light, longer shadows, painterly style"

6.3. Assessment Rubric

Table 6 summarizes the rubric utilized in Layer 4. All criteria are evaluated based on a scale of four levels. It is noteworthy that the rubric places emphasis on craft fundamentals, along with process and ethical considerations, such that the enhancement of computer-generated products alone cannot guarantee a top score.

Table 6. AADPP holistic assessment rubric (Layer 4).

Criterion	Level 1—Emerging	Level 2—Developing	Level 3—Proficient	Level 4—Distinguished
Observational accuracy	Proportions and edges weak; signs of tracing or AI dependence.	Most proportions present; edges and values inconsistent.	Sound proportions; controlled edges; readable value structure.	Highly accurate observation; confident edges and values.
Material handling	Medium controls the student; surface inconsistent.	Some control; surface and colour mixing acceptable.	Confident control; intentional surface and colour decisions.	Mastery of medium; surface integral to the work's meaning.
Conceptual development	Idea is generic or copied; weak development.	Idea identifiable; limited iteration.	Clear idea, evidence of iteration and refinement.	Original, well-developed idea sustained across the project.
AI literacy	AI use not understood; no critique of outputs.	Basic use; surface critique of outputs.	Effective use across workflows; substantive critique.	Sophisticated workflow; outputs critically translated into own practice.
Ethical transparency	No disclosure; AI use opaque.	Partial disclosure; ethical issues acknowledged but unexamined.	Full disclosure; ethical issues engaged in the journal.	Full disclosure; ethical reasoning shapes artistic decisions.
Process documentation	Journal absent or perfunctory.	Journal present; uneven detail.	Detailed journal; clear accept/reject decisions.	Exemplary journal: a discursive document in its own right.

6.4. Anticipated Outcomes and Educator Role

Based on patterns reported in comparable studies (Bian et al., 2025; Hutson & Cotroneo, 2023a, 2023b), the scenario anticipates several outcomes. Students who complete Layer 1 before encountering AI are expected to use AI more critically and to reject more AI outputs as too generic or homogenized, consistent with concerns raised in the literature (Desdevises, 2025; Sáez-Velasco et al., 2024; Wang et al., 2025). Process journals are expected to show iterative growth in prompt and workflow design (Hutson & Cotroneo, 2023b). The assessment rubric, by giving explicit weight to process and ethics, is intended to shift student attention away from polished AI surfaces toward demonstrable understanding (Heaton, 2025). These are anticipated patterns to be tested empirically in future work (Section 9.2).

The educator's role across the unit aligns with TPACK (Koehler et al., 2013; Mishra & Koehler, 2006) and UNESCO AI competency expectations for teachers (Miao & Holmes, 2024). In Layer 1, the educator acts as a traditional studio mentor; in Layer 2, the educator scaffolds prompt and workflow design and counters over-reliance; in Layer 3, the educator hosts critical dialogue and brings policy and legal contexts into the room; in Layer 4, the educator assesses both product and process and models reflective practice.

7. Comparing with Existing Studies

The AADPP model is compared with five categories of existing work. Table 7 summarizes the comparison along three axes: focal concern, treatment of foundational craft, and overall scope. The five comparison categories were not chosen arbitrarily: they correspond to the recurring clusters that emerged from the thematic synthesis of the 79-study corpus, and within each category the most representative and most frequently cited studies were selected as comparators. The three comparison dimensions were chosen because they directly test the central claim of the AADPP model, namely that foundational craft must be explicitly protected. Focal concern locates each approach's primary emphasis; treatment of foundational craft shows whether craft is protected or left implicit; and overall scope indicates how far each approach extends across a programme.

Table 7. Comparison of AADPP with representative existing approaches.

Approach (representative refs)	Focal concern	Treatment of foundational craft	Overall scope
Prompt-engineering pedagogy (Hutson & Cotroneo, 2023a, 2023b)	Iterative prompt design, AI-mediated ideation	Implicit; not explicitly protected	Narrow
AI literacy frameworks (Chee et al., 2025; Long & Magerko, 2020)	Competencies for recognizing and evaluating AI	Outside scope (domain-general)	Domain-general
Systematic reviews of AI in art education (Jiang et al., 2026; Lee & Palmer, 2025; Rong et al., 2025)	Mapping uses, benefits, limitations	Highlighted as concern; not modelled	Descriptive
Children-focused/equity work (Wang et al., 2025)	Cognitive homogenisation, equity	Implicit defence of traditional practice	Narrow
DSR + PRISMA precedents (Al-Dhaqm et al., 2017a, 2020, 2021a; Al-Mugern et al., 2024)	Conceptual model construction in adjacent fields	Not applicable (different domain)	Methodological
AADPP (this paper)	Integrating craft, AI ideation, ethics, and assessment	**Explicitly protected as Layer 1**	Integrative

7.1. Prompt-Engineering-Centred Pedagogy

Studies focused on prompt engineering and iterative AI ideation within digital art classrooms (Hutson & Cotroneo, 2023a, 2023b) inform Layer 2 but do not constitute a curriculum on their own. The AADPP model retains prompt and workflow engineering as central to Layer 2 but explicitly protects Layer 1 craft practice as a precondition. This addresses a recurring limitation of prompt-only approaches: students may achieve sophisticated prompts without developing observational or material competence.

7.2. AI Literacy Frameworks

Long and Magerko's AI literacy competencies and subsequent extensions (Chee et al., 2025; Long & Magerko, 2020) specify what learners should know about AI, but are not domain-specific to art. The AADPP model operationalizes AI literacy within the drawing and painting context by tying competencies to concrete studio activities and the assessment rubric in **Table 6**.

7.3. Systematic Reviews of Generative AI in Art Education

Recent systematic reviews (Jiang et al., 2026; Lee & Palmer, 2025; Rong et al., 2025) map the landscape of generative AI in art education but do not propose a unifying pedagogical model. The AADPP model contributes the missing artifact by synthesizing review findings into a deployable structure.

7.4. Children-Focused and Equity-Focused Work

Studies of AI painting tools for children raise concerns about cognitive homogenization, sampling bias, and theoretical fragility (Wang et al., 2025). The AADPP model addresses these by making homogenization an explicit topic of critical reflection in Layer 3 and by requiring divergent ideation in Layer 2. The model can be adapted to younger learners by scaling complexity and tightening teacher mediation.

7.5. Methodological Precedents in Adjacent Domains

The design-science and metamodel-validation work in digital forensics provides a methodological template for the present study (Al-Dhaqm et al., 2017a, 2017b, 2020, 2021a; Al-Mugern et al., 2024). The validation pattern—face validation, comparative analysis, and case-study demonstration—is directly transferable to pedagogical artifacts and is adopted here.

8. Results and Discussion

Three results emerge from the combined PRISMA and DSR work.

First, the systematic synthesis confirms that generative AI is already deeply present in visual arts education, but its integration remains theoretically fragmented and often confined to single courses, tools, or dimensions, such as prompt engineering or ethics (Jiang et al., 2026; Lee & Palmer, 2025; Rong et al., 2025). There is a documented gap for a unifying pedagogical artifact that integrates skill, ideation, critique, and ethics across a programme.

Second, the AADPP model addresses that gap by combining four interrelated layers anchored in established theory and evaluated by face validation, comparative analysis, and case-study demonstration. The primary contribution of the model rests in the explicit protection of foundational craft (Layer 1), which is essential for meaningful engagement with artificial intelligence (AI). Specifically, this strategy addresses a concern raised in various studies, namely, that AI-rich curricula could produce students capable of creating complex prompts and images but unable to replicate their observations (Desdevises, 2025; Heaton, 2025; Wang et al., 2025). By establishing Layer 1 as a protected analogue space, the model ensures the preservation of the embodied component of art creation, alongside serious involvement in AI, from image-to-image manipulation to structural conditioning, keeping the pupils' drawings in the loop.

Third, the example case study demonstrates the model's viability within a regular 12-week unit. The inclusion of process journals, the assignment of weights to ethics and AI literacy apart from craft, as well as the requirement to reveal all AI usage, reflects emerging institutional norms (Jung & Yoon, 2025) and guidelines by UNESCO and the OECD (Miao & Holmes, 2024; OECD, 2023). There are several potential issues identified in the discussion: teachers' inability to have the necessary TPACK for Layers 2 and 3 due to lack of professional development opportunities (Miao & Holmes, 2024; Mishra & Koehler, 2006). Furthermore, equity concerns affect the unit in terms of AI choice, availability of local computational facilities, and whether the assessed output can be produced using free or open-source tools. These aspects impact the inclusivity of the learning experience.

Finally, the most significant implication concerns the changing role of the teacher. As AI allows for greater flexibility in producing images, teaching becomes the task of fostering judgment regarding when AI serves and when it hinders progress. Moreover, the instructor teaches the learners what constitutes their own creative output, which goes beyond crafting. Such an expanded role is articulated in the four layers of the AADPP framework.

9. Limitations and Future Empirical Work

9.1. Limitations

Several limitations apply to this study. First, the evaluation relies on face validation, comparative analysis, and an illustrative case-study scenario rather than a controlled empirical experiment; the case study does not report participant data, and "anticipated outcomes" are derived from comparable studies rather than from new measurement.

Second, the literature on generative AI in art education is expanding rapidly. A model built on 2019-2026 literature must be revisited as new tools and pedagogical practices emerge. Specific features (named tools, specific prompt-engineering patterns) will date faster than the four-layer structure, which is intended to remain stable.

Third, the model assumes baseline access to AI tools, hardware, and trained instructors. In resource-constrained contexts these assumptions may not hold, and equity-of-access considerations require continuing work (Miao & Holmes, 2024).

Fourth, the model is grounded in foundation-level studio practice in higher education. Adaptations to K–12, community-arts, and self-directed learner contexts will require further design iterations and evaluation, particularly with respect to child safety, developmental appropriateness, and parental involvement (Wang et al., 2025).

Fifth, while the methodological lineage of PRISMA + DSR with multi-method validation is well established (Al-Dhaqm et al., 2017a, 2020, 2021a; Page et al., 2021a; Peffers et al., 2007), its transfer from technical domains to a humanistic, embodied practice such as drawing and painting introduces translation risks. Future work should examine whether art-specific validation criteria—for example, criteria centred on aesthetic development or studio-culture fit—should be added to the standard set used here.

Sixth, the PRISMA review described here was not protocol-registered (for example, with PROSPERO), and inter-rater reliability statistics are not reported. Future systematic reviews extending this work should preregister their protocols and explicitly report screening reliability.

9.2. A Design for Future Empirical Work

An empirical study to test the AADPP model would adopt a mixed-methods, multi-site design across at least three art schools or university foundation programmes, with cohorts of approximately 25 students each over one or two semesters. A quasi-experimental comparison would contrast AADPP-aligned units with parallel units using either traditional pedagogy or unstructured AI integration. Pre- and post-tests would assess observational drawing skill (using rubric-based ratings of standard subjects), AI literacy (using established instruments), and ethical reasoning (using vignette-based assessments). Process journals and final portfolios would be analyzed qualitatively for evidence of iterative growth in prompt and workflow design and for the quality of accept/reject decisions. Educator focus groups would assess feasibility and TPACK readiness.

Outcome measures would include: 1) measurable change in observational drawing skill, 2) AI literacy scores, 3) ethical reasoning quality, 4) creative outcome ratings using the Consensual Assessment Technique (Amabile, 1982), and 5) student self-efficacy and continuance intention measures consistent with the TAM tradition in this domain (Sun et al., 2025). The study would be preregistered and conducted with appropriate ethical clearance.

10. Conclusion

In today's fast-changing art education landscape, generative AI tools in drawing and painting are quickly adopted without a coherent framework. Based on the principles of Design Science Research and a systematic PRISMA analysis of the literature, the AI-Augmented Drawing and Painting Pedagogy (AADPP) model is proposed, conceptually evaluated, and demonstrated. It has four distinct layers-craft development, AI-facilitated ideation, ethical evaluation, and reflection-which are underpinned by three main concepts-human primacy, transparency, and iteration. The key proposition behind AADPP is that successful incorporation of AI requires the establishment of a unique pedagogical layer dedicated to preserving foundational craft. Grounded in constructivism, TPACK, AI literacy, and observational drawing, this model considers AI an additional tool that enhances, not replaces, physical experience. Conceptual face validation through six criteria, comparison with five previous frameworks, and demonstration via a unit of learning over 12 weeks, including specific prompts, a detailed rubric, and a guide for process journals indicate that AADPP is conceptually coherent and practical to be implemented in university drawing and painting studios. The contributions to knowledge include: first, the combination of relevant literature, including prompt engineering, AI literacy, creative assessment techniques, and ethics in design into a single artifact; second, the explicit protection of Layer 1 of AADPP as an analogue space; and third, the tangible tools to operationalize AI literacy-workflow, process journal template, assessment rubric, and a 12-week curriculum. Limitations of this work consist of reliance on conceptual validation through face validation, comparison, and illustration, assumptions regarding access to resources (generative AI tools, hardware, and training educators), as well as applicability of this framework exclusively in higher education settings. Such limitations do not detract from the overall contribution but suggest further development and testing of AADPP in other settings. Potential next steps include conducting an empirical study, creating instructional materials for teachers' professional development, expanding the application to new AI generations, and generalizing to new contexts such as secondary education and community art programs.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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