

Article

AI Literacy Facets in Design Education: A PLS-SEM Study of Learning Performance and Academic Well-Being

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Received: 09 October 2026 / Accepted: 11 October 2026 / Published: 12 October 2026

Abstract: Artificial intelligence (AI) is swiftly transforming design practice and, consequently, the skills anticipated of design students. Instead of perceiving AI literacy as a singular metric, recent research conceptualises it as a constellation of interrelated facets, including knowledge of AI, awareness of its affordances and limits, critical reflection, operational ability, ethical awareness, and emotional adaptability. This study examines how these facets jointly relate to learning performance and academic well-being in design education. We conducted a cross-sectional online survey with 475 students enrolled in design and related programmes in the United Kingdom, other European countries, and Australia. Employing Partial Least Squares Structural Equation Modelling (PLS-SEM), we initially confirmed robust reliability, convergent validity, and discriminant validity for all constructs. The structural model demonstrated an adequate fit and considerable explanatory capability (R^2 for endogenous variables ranged from 0.62 to 0.78, with all $Q^2 > 0$). Three primary patterns emerged. First, AI knowledge operates as an upstream resource that strengthens awareness, critical reflection, operational ability, and ethical awareness, rather than functioning as a stand-alone dimension. Second, learning performance is primarily driven by a “recognise–reflect–produce” chain in which awareness and critical reflection mediate the effects of knowledge and operational skills on performance. Third, ethical awareness contributes more strongly to academic well-being than to performance, with learning performance and ethical clarity jointly supporting students’ positive experiences. These findings suggest that effective AI integration in design education requires knowledge-first curricula, studio tasks that explicitly scaffold awareness and reflection, and ethics teaching that protects students’ sense of fairness, authorship, and emotional safety.

Keywords: AI literacy; Design education; Generative AI; Learning performance; Academic well-being

1. Introduction

Artificial intelligence (AI) has significantly revolutionised the design sector: from sourcing inspiration and creating mood boards to idea sketching, prototyping, rendering, organisation, and critique, AI is now present at nearly every phase. This sector-wide transition has significant consequences for design education, necessitating the preparation of students for an evolving professional environment. Proficiency with tools alone does not guarantee improved learning. The matter at hand is AI literacy—the capacity to comprehend the workings of AI, discern its optimal applications, select and adjust tools wisely, grasp concerns related to privacy, authorship, and bias, critically evaluate outputs, and maintain composure and control in the face of unexpected results (Ng et al., 2021; Ng et al., 2024).

Design learning is characterized by exploration through openness, aesthetic judgment, and iterative refinement. Historically, the genesis of a design idea was a deeply tactile and embodied process (Kirsh, 2013). It relied on the direct manipulation of physical media—the graphite of a pencil on paper, the shaping of clay, or the assembly of physical mockups. In this paradigm, the designer's hand functioned as the principal interface between abstract concepts and physical manifestation, with manual skill inherently connected to creative expression (Iranmanesh & Lotfabadi, 2025). The emergence of generative AI has catalysed a paradigm shift, transferring the focus of production from manual effort to linguistic expression (Barandiaran & Pérez-Verdugo, 2025). The iterative process of drawing is progressively being complemented, or in some cases substituted, by the skill of prompt engineering (Tan & Luhrs, 2024). The fundamental talent has shifted from merely drawing to the ability to express a vision through exact textual or parametric commands, thereby facilitating a strategic interaction with the machine. Students are now increasingly co-creation with AI, instigating a paradigm shift that transfers the focus of production from manual effort to linguistic expression. This innovative co-creation technique has notable benefits, including expedited divergence, improved graphics, and diminished iteration time (Tan & Luhrs, 2024). However, it also presents considerable hazards, including as homogenisation, over-reliance, biased data, and ambiguity regarding authorship (Long & Magerko, 2020).

Several frameworks and instruments for AI literacy have been proposed in the fields of higher-education research. These frameworks consistently recognise essential dimensions including the practical application of AI, the capacity to detect its presence, ethical considerations, and related competencies such as problem-solving and emotional regulation (Ayanwale et al., 2024). This study utilises the MAIILS framework, which conceptualises artificial intelligence literacy through “using and applying”, “understanding and comprehending”, “detecting artificial intelligence”, and “ethical considerations of artificial intelligence”, and which is particularly suitable for design students because it explicitly links these literacy dimensions to socio-emotional competencies such as problem-solving, self-efficacy, persuasive skills, and emotional regulation (Carolus et al., 2023). Together, these dimensions provide the conceptual basis for our assessment. Nonetheless, in design education, we still lack empirical evidence about which dimensions of AI literacy most strongly influence design students’ learning outcomes and academic well-being, how these effects operate. Whether different groups of students benefit in different ways also remains an open question for future research.”

2. Literature Review

2.1 The Need for a Multidimensional AI Literacy Approach in Design Education

Artificial intelligence is transforming professional design approaches and revolutionising design education through real-time analysis and the creation of innovative forms (Bora & Kölemen, 2025). Consequently, AI literacy has evolved from a supplementary skill to an essential competency for design students. Core accounts in HCI characterise literacy as capacity to comprehend the nature and functioning of AI, evaluate its strengths and weaknesses, appropriately utilise and calibrate tools, and critically consider ethical, bias-related, and societal implications (Long & Magerko, 2020). Scoping reviews also highlight significant conceptual variability in the definitions and measurements of AI literacy, suggesting that empirical studies should transcend aggregate scores and investigate facet-level relationships with specific outcomes (Laupichler et al., 2022; Zhang, Ganapathy Prasad, & Schroeder, 2025). This detailed approach is particularly relevant in art and design education (Järvelä et al., 2023; Norris et al., 2025). Students participate in many activities, including selecting suitable tools, composing effective prompts, curating AI-generated options, and validating authorship, each requiring a

unique set of AI-related competencies (Tsao & Nogues, 2024). Therefore, a facet-level analysis of AI literacy extends beyond basic student classification, providing a more powerful explanatory framework for comprehending their performance and decision-making processes (Ng et al., 2024).

2.2 A Framework for Analyzing AI Literacy: Aligning Competencies with Design Pedagogy

Comprehensive AI literacy empowers individuals to critically analyze AI technologies, communicate and collaborate productively with AI, and effectively use AI as a tool in diverse contexts, including online platforms, home environments, and professional workplaces (Ayanwale et al., 2024). Across higher education, AI literacy is increasingly framed as a constellation of interrelated competencies rather than a single global trait (Chee et al., 2025). Validated instruments make such analyses tractable (Laupichler et al., 2023). Previous frameworks, such as the Meta Artificial Intelligence Literacy Scale (MAILS), demonstrate that AI literacy can be categorised into multiple competencies, with terminology differing among frameworks. Most studies in teacher education are grounded in the Technology Pedagogical Content Knowledge (TPACK) framework, which encompasses essential aspects of AI literacy, including technical expertise, ethical considerations, and practical application skills (Ayanwale et al., 2024). Research in computer science considers high-level AI-related skills (creation and evaluation of AI) as components of AI literacy (Lintner, 2024). The definition of AI literacy varies by field and target population (Almatrafi et al., 2024), but generally emphasizes "critical thinking," "collaborate effectively with AI," and "ethical awareness." While numerous frameworks exist, the conceptualization by Carolus et al. (2023), which organizes AI literacy into multiple competencies such as AI operational ability, AI critical reflection, AI knowledge, AI awareness, AI ethical awareness, and AI emotional adaptability, provides a particularly relevant foundation for this study. Their distinction between operational skills and judgment-oriented competencies aligns well with the pedagogical goals of design education (Ghajargar & Bardzell, 2019). This conceptual division between operational and judgment-oriented competencies aligns well with the core pedagogical loop of the design studio (McLaughlan & Lodge, 2019). Students learn through an iterative process of 'making and improving,' which necessitates both the operational skills to generate and manipulate artifacts (e.g., creating variations with generative AI) and the analytical acumen to assess, choose, and refine those outputs into a coherent final product.

2.3 From Literacy Facets to Learning Performance

Two complementary theoretical strands clarify how AI literacy may shape learning performance in design programs. First, Cognitive Load Theory (CLT) and the Cognitive Theory of Multimedia Learning (CTML) hold that performance improves when learners reduce extraneous load, manage intrinsic load, and invest freed resources into germane processing (Sweller et al., 1998; Mayer, 2002). In AI-rich studios, students with strong operational ability can deploy tools to externalize low-value work (e.g., scaffolding alternatives, rendering variants) without overwhelming attention. Students possessing critical evaluation skills—often captured under “understanding” or “critical reflection”—are better positioned to scrutinize outputs, check provenance, and align representations with objectives, thereby transforming efficiency improvements into profound learning rather than mere superficial throughput.

While CLT explains the underlying cognitive mechanics, Self-Regulated Learning (SRL) frameworks provide the macro-level lens, explaining how competencies translate into achievement through forethought, performance, and self-reflection cycles (Stoeger & Zeidner, 2019). In SRL, self-efficacy is a proximal driver of strategy deployment and persistence (Zimmerman, 2002), while planning, monitoring, and regulation are assessable components that account for variance in college learning (Pintrich, 2004). Facet-level literacy—especially

knowledge of AI, operational ability, and AI awareness—should scaffold better goal setting, tool-task fit, and monitoring during co-creation with AI. To locate where these competencies matter within studio tasks, we next consider how creative work unfolds across distinct phases.

Building on creative-cognition theories, studio work can be viewed as two linked phases: generative (producing numerous preliminary options) and evaluative (refining and enhancing them) (Finke, Ward, & Smith, 1996). In this context, operational capability and AI awareness primarily support the generative phase by producing and organizing options, whereas knowledge of AI, critical reflection, and ethical awareness guide the evaluative phase by judging feasibility, appropriateness, and responsibility (Tadimalla & Maher, 2025). This mapping elucidates why certain characteristics are more closely related to performance than others, and why their effects may be synergistic rather than merely cumulative.

2.4 Student Well-being in the Age of AI

Design programs also prioritize academic well-being—e.g., sustained engagement, interest, perceived control, and manageable strain (Kern et al., 2016; Klimova & Pikhart, 2025). Control-Value Theory (CVT) posits that achievement emotions arise from appraisals of perceived control over tasks and subjective value attached to outcomes; these emotions in turn shape engagement and achievement (Pekrun, 2006). Within this perspective, AI emotional adaptability is a component closely related to academic well-being: it stabilizes affect under uncertainty, increases perceived control, and reduces strain during verification (Zhang & Liu, 2025). In AI-rich studios, several aspects of AI literacy can enhance students’ perceived control and task value. AI knowledge and AI awareness help students anticipate model behaviour and verify outputs, demystifying the ‘black box’ (Bearman & Ajjawi, 2023). Ethical awareness clarifies acceptable boundaries and reduces the moral ambiguity and uncertainty that can arise during critique and evaluation (Corbin et al., 2025). Operational ability makes routes to polished artefacts more visible and attainable, thereby increasing the perceived value of the task, while critical reflection helps align AI-generated outputs with project objectives and evidence, further reinforcing perceived control (Kim & Maher, 2023). CVT thus offers a principled route from literacy to well-being: AI literacy shapes appraisals of control and value, which in turn influence achievement emotions, engagement and, ultimately, performance.

2.5 Boundary Conditions for AI Use in Design Studios

Simultaneously, human-automation research highlights two contrasting pitfalls that may diminish the advantages of AI literacy, suggesting that these benefits are contingent upon how learners interact with AI tools and are not inherently advantageous in every context (Hermann, 2023). Drawing upon research in human-automation interaction, cognitive science, and affective computing, we delineate several boundary conditions that can moderate these benefits at the behavioral, cognitive, and situational levels (Lucas et al., 2024). Automation bias describes over-reliance on algorithmic suggestions and under-weighting of disconfirming cues, yielding errors of omission and commission (Parasuraman & Riley, 1997). Conversely, algorithm aversion shows that individuals may dismiss algorithms after observing an error, even when the algorithm outperforms humans on average (Dietvorst, Simmons, & Massey, 2015). In design studios, both phenomena can impair learning: uncritical acceptance diminishes authorship and critical judgment, whereas blanket rejection forfeits real advantages (e.g., rapid divergent exploration). Thus, AI awareness and critical reflection are central safeguards for healthy orchestration rather than mere supplementary elements. From a cognitive-load perspective, CLT/CTML also caution that poor alignment between representations and goals, or the introduction of redundant cues, can inflate extraneous load; thus, the payoffs of operational ability and knowledge of AI are stronger under high task complexity and verification load, and weaker in simple, low-stakes tasks

(Sweller et al., 1998; Mayer, 2002). In situations of time constraints or severe criticism, AI's emotional adaptability can mitigate stress and facilitate benefits materialize, as indicated by recent evidence on AI-mediated learning environments and students' emotional well-being (Zhang & Liu, 2025). Although not explicitly examined in our model, these boundary underscore the intricate nature of AI integration and will provide a theoretical foundation for our analysis of the results.

2.5 The Present Study and Hypotheses

Our study focuses specifically on how design students develop AI literacy within this changing context. While our framework is conceptually informed by prior work, the six-facet structure used in this study was developed and validated independently—AI knowledge (AIK), operational ability (OP), AI awareness (AWA), critical reflection (CR), ethical awareness (ETH), and AI emotional adaptability (EA) (e.g., Carolus et al., 2023). In the present study, we tailor this six-facet structure to studio-based design learning. We treat each facet as a resource that supports specific stages of AI-supported studio work and provides distinct pathways to learning performance and academic well-being.

Design learning hinges on iterative studio work and critique. Mapping our facets onto this workflow clarifies which ones are closest to which outcomes:

Operational ability (OP) lowers extraneous load and supports productive iteration, enabling the cycles that feed critical reflection.

AI awareness (AWA) organizes the generative stage by keeping students mindful of how AI shapes options and when verification is needed, thereby triggering CR.

Critical reflection (CR) is proximal to LP: it structures originality/provenance checks and alignment with project goals, translating orchestration into quality.

AI knowledge(AIK) calibrates expectations and prevents misuse or blanket rejection, providing a foundation for ETH, AWA, CR, and OP.

Ethical awareness (ETH) clarifies boundaries around authorship, attribution, fairness, and acceptable use, which supports both LP (fewer rework/penalties).

AI emotional adaptability (EA) stabilizes affect under time pressure and during critique, making it especially proximal to WB and also helpful for sustained engagement in revision.

Taken together, these points justify analyzing dimension-level paths from AIK, OP, AWA, CR, ETH, and EA to LP and WB, with the indirect routes specified above. Because LP and WB are closely intertwined in studio courses, we treat them as positively associated in the structural model; in robustness checks we examine alternative directional specifications

3. Methods

3.1 Participants

This study employed a cross-sectional online survey targeting undergraduate and graduate students in design and related disciplines. During a single academic term, the questionnaire was disseminated once through department- and course-related channels (e.g., course groups and social media) and hosted on Wenjuanxing and Google Forms to broaden coverage. Before participation, respondents read a concise information sheet describing the study purpose, potential risks, privacy safeguards, and the right to withdraw, and then provided informed consent. In total, 556 responses were collected. Among these, 554 participants consented to complete the survey. Of this group, comprising 286 female (51.62%), 251 male (45.30%), and 17 who preferred not to disclose (3.07%). The sample was predominantly young: 18–22 years, 364 (65.70%); 23–25 years, 130 (23.47%); ≥ 25 years, 55 (9.93%); and ≤ 18 years, 5 (0.90%). By study level, there were 248 first- and second-year undergraduates (44.77%), 127 third- and fourth-year undergraduates (22.92%), 137 master's students (24.73%), and 42 doctoral students (7.58%). The

breadth and variation across gender, age, and study level, as well as the inclusion of students from universities in several countries and regions, provide initial support for the external validity and generalizability of the findings to the broader population of design students. Applying predefined data-quality criteria (e.g., exceptionally brief completion times and apparent problematic response patterns), we excluded invalid cases, resulting in an analytic sample of 475 for subsequent analyses.

3.2 Data collection

We assessed the fundamental constructs using a consistently formatted questionnaire. All items employed a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) and were positively worded. The questionnaire was developed in both Chinese and English and subsequently finalized following a minor pretest. In the formal administration, participants initially completed demographic items and then proceeded through the scales in a predetermined sequence.

AI Literacy Scale. AI literacy was assessed using a set of items developed for this study on the basis of recent AI literacy frameworks and scales (Almatrafi et al., 2024; Ayanwale et al., 2024; Chee et al., 2025; Gümüş & Mehmet, 2025; Lintner, 2024; Tadimalla & Maher, 2025). The items encompass six dimensions: AI knowledge, operational ability, AI awareness, critical reflection, ethical awareness, and AI emotional adaptability. Before structural modelling, we conducted item-level quality assessments and refined the scale. Items showing weak conceptual alignment or low factor loadings (e.g., ETH2, ETH3, AWA6) were removed, and the measurement model was re-estimated. The final scale demonstrated satisfactory internal consistency, convergent validity, and discriminant validity relative to the other constructs.

Academic Well-Being (WB) Scale. This scale evaluates students' subjective experiences during learning (e.g., engagement, positive affect, and sense of purpose). In the structural model, WB was specified as a distal outcome latent construct that is predicted by learning performance (LP).

Learning Performance (LP) Scale. This scale evaluates learning outcomes, including task quality, perceived achievement, and self-evaluation. In the structural model, LP was designated as the primary outcome of the AI literacy facets and as the direct predictor of WB, consistent with the hypothesised LP → WB pathway.

Table 1 Test Results

Scale	No. of items	Factor loadings	Cronbach α	CR	AVE
AIK	3	0.868–0.874	0.842	0.904	0.759
OP	3	0.850–0.876	0.899	0.747	0.899
AWA	3	0.843–0.883	0.897	0.745	0.897
CR	3	0.879–0.895	0.918	0.788	0.918
ETH	3	0.839–0.877	0.894	0.737	0.894
EA	3	0.870–0.902	0.912	0.776	0.912

LP	4	0.851–0.885	0.925	0.755	0.925
WB	4	0.853–0.864	0.880	0.917	0.735

To ascertain the quality of all scales, we evaluated internal consistency, convergent validity, and discriminant validity prior to structural modelling. Table 1 presents an overview of essential psychometric indices for each scale, with comprehensive results described in the results **section**.

3.3 Data analysis

This study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM, SmartPLS) within the same framework to perform two objectives: first, to evaluate the reliability of the scales, and second, to analyze the relationships among the variables. Prior to modeling, we meticulously cleaned and arranged the raw data in accordance with predetermined criteria: invalid responses were eliminated, and missing values and anomalies were scrutinized and addressed. Subsequently, the scales underwent a quality assessment and refinement: the alignment of each item with its respective construct was evaluated, and underperforming items (e.g., ETH2, ETH3, AWA6) were eliminated. The scale was then re-estimated to ensure optimal performance regarding consistency, convergent validity, and discriminant validity prior to structural analysis.

Measurement Model Evaluation. We assessed the measurement model according to three key criteria: (1) internal consistency, which evaluates whether items within a scale are strongly highly correlated; (2) convergent validity, which verifies that items effectively measured their intended underlying construct; (3) discriminant validity, ensuring that each construct was distinct from others in the model. If an item substantially compromised any of these criteria, we implemented a remove-re-estimate-review procedure until all scales met established methodological standards. All diagnostic assessments and corresponding outcomes (e.g., factor loadings, reliability metrics, validity indicators) are documented in the Results section to support verification and reproducibility.

Structural Model Evaluation. Guided by the theoretical model, we assessed the direct and indirect effects among the core constructs. For each path, we reported the standardized coefficient (β), significance (t/p), and 95% confidence interval as shown in the analysis outputs. We further evaluated the model's performance by analyzing the explanatory power of endogenous constructs (R^2 , adjusted R^2), their predictive relevance (Q^2), and overall fit indices (SRMR; NFI, d_ULS, d_G as references).

Robustness and Sensitivity Analyses. To guarantee that the conclusions are not contingent upon a single specification, we performed multiple robustness checks: (1) we removed borderline items and re-estimated the model to see whether the primary conclusions held. (2) we evaluated plausible alternative specifications (e.g., trimming non-essential links) and compared outcomes. (3) we omitted potentially problematic responses (e.g., extremely brief completion times or straight-lining) and re-estimated the model to assess whether the direction and significance of key paths remained stable. (4) we conducted standard methodological diagnostics (e.g., screening for overly similar items). If the primary findings remained consistent across these variations, we considered the conclusions robust.

4. Results

Describe the statistical methods used to analyze the data. Specify the software used and the specific statistical tests performed.

4.1 Measurement Model

Utilizing the final dataset comprising 475 valid responses from students in design and related disciplines across various nations and locations, we initially analyzed descriptive statistics for the sample and study variables. The respondents varied across countries/regions, gender and study level, and the construct means clustered around the midpoint of the five-point scale with adequate standard deviations, indicating a diverse sample and sufficient variability for further research.

We assessed reliability and convergent validity (Table 2). All standardized factor loadings exceeded 0.83, exceeding the recommended 0.70 threshold. Cronbach' s α values ranged from 0.842 to 0.925, and composite reliability (CR) ranged from 0.737 to 0.917, all beyond the recommended 0.70, indicating good internal consistency. Average variance extracted (AVE) values ranged from 0.735 to 0.918, all exceeding 0.50, supporting convergent validity.

Table 2 Scale items and convergent validity analysis.

Constructs	Codes	VIF	λ	α	CR	AVE
AIK	AIK1	3.716	0.872	0.842	0.904	0.759
	AIK2		0.868			
	AIK3		0.874			
AWA	AWA2	3.455	0.843	0.897	0.745	0.897
	AWA4		0.862			
	AWA5		0.883			
CR	CR1	4.167	0.895	0.918	0.788	0.918
	CR2		0.879			
	CR3		0.890			
EA	EA1	3.913	0.870	0.912	0.776	0.912
	EA2		0.902			
	EA4		0.870			
ETH	ETH1	3.440	0.839	0.894	0.737	0.894
	ETH4		0.858			
	ETH5		0.877			
LP	LP1	3.204	0.885	0.925	0.755	0.925
	LP2		0.870			
	LP3		0.868			
	LP4		0.851			
OP	OP2	3.303	0.867	0.899	0.747	0.899
	OP3		0.876			

	OP5		0.850			
WB	WB1	3.753	0.857	0.880	0.917	0.735
	WB2		0.864			
	WB3		0.853			
	WB4		0.855			

Discriminant validity (Table 3) was supported by the Fornell–Larcker criterion: for each construct, the square root of its AVE (on the diagonal) exceeded its correlations with other constructs (off-diagonal). We also assessed multicollinearity among latent variables (Table 2). The highest VIF values (3.204 – 4.167) were below the recommended threshold of 5, suggesting multicollinearity was not an issue.

Table 3 Fornell-Larcker criterion.

	AIK	AWA	CR	EA	ETH	LP	OP	WB
AIK	0.871							
AWA	0.813	0.863						
CR	0.790	0.823	0.888					
EA	0.785	0.806	0.819	0.881				
ETH	0.790	0.808	0.810	0.771	0.858			
LP	0.789	0.798	0.824	0.829	0.762	0.869		
OP	0.803	0.786	0.769	0.789	0.752	0.796	0.864	
WB	0.814	0.815	0.796	0.810	0.802	0.830	0.818	0.857

4.2 Model Fit, Explanatory Power, and Predictive Relevance

As demonstrated in Table 4, the model fit was satisfactory: SRMR = 0.038 (< 0.08). The d_ULS = 0.515 and d_G = 0.474 indices were significantly below the 95% bootstrap quantile thresholds, and NFI = 0.877 (> 0.80), collectively indicating an acceptable model fit.

Table 4 Model' s fit.

	Fit indices
SRMR	0.038
d_ULS	0.515
d_G	0.474
NFI	0.877

Concerning explanatory power (Table 5), R² for endogenous constructs ranged from 0.624 to 0.773 (adjusted R² similar), all over 0.50, thereby indicating a substantial proportion of explained

variance; notably, WB exhibited the highest $R^2 = 0.773$. For predictive relevance, all Q^2 values were positive (about 0.457–0.580), signifying strong predictive relevance. Together, the structural model demonstrates a reasonable fit, substantial explanatory capacity, and sufficient predictive validity.

Table 5 Explanatory power, and predictive power.

	Q^2	R^2	Adjusted R^2
AWA	0.488	0.660	0.660
CR	0.574	0.733	0.732
ETH	0.457	0.624	0.624
LP	0.580	0.776	0.774
OP	0.478	0.645	0.644
WB	0.562	0.773	0.772

Overall, the mediation results indicate that AI knowledge (AIK) reaches learning performance (LP) indirectly via critical reflection (CR) and via the pathway from AI awareness (AWA) to critical reflection. Additionally, operational ability (OP) impacts learning performance through critical reflection, whereas ethical awareness (ETH) only mediates the relationship between AI knowledge and academic well-being (WB), without affecting the link between AI knowledge and learning performance.

5. Discussion

5.1 Findings of Research and Importance

Based on a sample of design and related majors, this study employed PLS-SEM to evaluate both measurement quality and structural paths. Three mutually reinforcing conclusions arise:

(1) AI knowledge (AIK) is an upstream driver. It directly enhances AI awareness (AWA), critical reflection (CR), and operational ability (OP), while also impacting learning outcomes through these mediators. The notable positive effect of AIK on ethical awareness (ETH) suggests that knowledge and normative awareness are interconnected.

(2) The fundamental pathway of learning performance (LP) is “recognize → reflect → produce.” The chains of both $AIK \rightarrow CR \rightarrow LP$ and $AIK \rightarrow AWA \rightarrow CR \rightarrow LP$ are significant, and OP has a dual channel of $OP \rightarrow LP$ and $OP \rightarrow CR \rightarrow LP$. In other words, going from “knowing” to “producing” requires a multi-step conversion of the process of cognizing → reflecting → operating.

(3) Ethical awareness (ETH) results in experience rather than performance. $ETH \rightarrow WB$ is significant, whereas $ETH \rightarrow LP$ is negligible; coupled with the distinctly positive $LP \rightarrow WB$ path, this indicates a “do well → feel better” coupling whereby high-quality output and normative clarity collectively enhance academic well-being.

These findings highlight the intrinsic significance of process capabilities: AI awareness (AWA) assists learners in recognizing the limitations and circumstances of AI utilization; Critical reflection (CR) facilitates higher-order judgment and self-verification; Operational ability (OP) guarantees execution. Together, three transforms AIK into consistent output quality and positive experience. Ethics awareness contributes not by “raising scores” but by fostering a secure,

equitable, and manageable learning environment that promotes well-being—aligning with contemporary priorities on safe, responsible, and sustainable practices in education.

5.2 Discussion with Previous Work: Confirmations and Extensions

Initially, concerning the knowledge-strategy-outcome chain, previous research often treated critical reflection as a single mediator. By prioritizing awareness prior to reflection, we support with empirical evidence a sequence of “recognize first, then reflect” —an important guide for course design. Second, regarding the role of ethics, some work assumes that improved ethics leads to improved performance. However, in the present design context, ethics awareness has stronger effect on subjective experience, endorsing a “ethics → well-being” pathway and cautioning against instrumentalizing ethics training as a “shortcut to higher scores.” Third, regarding operational capability, OP primarily demonstrates direct effects on output in existing studies, and we further recognize the indirect enhancement of LP through triggering reflection—OP→CR— “to use and to review” are interconnected rather than distinct.

5.3 Implications for Teaching and Learning Processes

AI-supported assignment work is not a “black box” from the process perspective. Our processes suggest that identifying where AI intervenes → recognizing potential risks → conducting factual and logical checks → revising accordingly are shared steps leading to high-quality work. If instruction focuses solely on tool skills, students may develop the misconception of being “fast but inaccurate”; only when awareness and reflection within assignments are standardized and proceduralized will students internalize these into stable capabilities. This also elucidates why LP→WB will be significant: in instances where students can explain their completion of work, with full control and reliability, their well-being will inherently improve.

5.4 Additional Remarks: Emotion–output Coupling and Norms–experience Coupling

Two significant couplings arise from this: Output–experience linkage (LP→WB): an individual's sense of control and achievement about their output is a significant source of positive learning emotions. Norms–experience linkage (ETH→WB): ethical awareness reduces uncertainty and anxiety about the threat of being questioned, further enhancing classroom safety and classroom trust. These couplings indicate that optimization of teaching goals should support “can do it well” and “feel good” with one other, rather than trading off efficiency against experience.

6. Implications

This study provides substantial theoretical insights and actionable practical pedagogical recommendations for integrating AI into design education. Its principal theoretical contribution is the delineation and empirical validation of a fundamental process chain: “awareness → reflection → production.” By demonstrating that AI awareness (AWA) serves as a crucial antecedent to critical reflection (CR), our model refines the vague “AI literacy → learning outcomes” pathway into a more testable and operational sequence. This discovery has direct implications for curriculum development. Instead of focusing merely on operational skills, educators should implement a structured, four-step pedagogical framework that reflects this cognitive process: (1) explicitly instructing students to pinpoint and annotate the utilization of AI; (2) requiring them to verify the accuracy and source of AI-generated content through evidence checks; (3) promoting reproducible operations through tools like prompt logs and version histories; and (4) concluding with a structured summary of reflection. To reinforce this process, assessment rubrics should be realigned to dedicate a significant portion of the grade (e.g., 20–30%) to the quality of students' awareness and reflection processes, rather than evaluating only the final product.

A second significant addition is the conceptualizing of learning outcomes as a dual dimension, encompassing both learning performance (LP) and academic well-being (WB). Our findings demonstrate a vital distinction: although the awareness-reflection-operation chain primarily influences performance, ethical awareness (ETH) serves as a more robust predictor of well-being. This “ethics for experience, not for scores” insight cautions against instrumentalizing ethics training merely as a means to improve grades. Instead, the strong ETH→WB path suggests that embedding ethical discussions—around authorship, bias, and fairness—into classroom scenarios serves a more profound purpose: fostering a sense of psychological safety, fairness, and control, which in turn enhances students' positive learning experiences. This is further reinforced by the positive LP→WB path, indicating a virtuous cycle where high-quality, well-understood work enhances well-being. Educators can leverage this by using milestone critiques and showcases to make progress visible, thereby stabilizing well-being and creating a positive feedback loop between achievement and emotion.

Finally, our model regards AI knowledge (AIK) not as a direct performance driver, but as a fundamental, upstream resource that systematically enables all other facets of literacy, including ethical awareness, critical reflection, and operational ability. This layered view offers a clear justification for tiered intervention. Effective AI pedagogy should begin with building a solid knowledge base to calibrate student expectations and prevent misuse. Building on this foundation, instruction can then focus on cultivating awareness and reflection through scaffolded tasks. Only then can operational practice be enhanced, enabling students to convert tool proficiency into genuine creative and academic gains. This tiered approach also informs teacher development, which must move beyond simple tool training to include comprehensive seminars on instructional design and assessment that correspond with the awareness-reflection-operation sequence.

7. Limitations & Future Research

While this study provides a robust foundational model, its limitations highlight important avenues for future research. First, the cross-sectional design, despite its suitability for initial model testing, cannot definitively establish causality. The directions of the paths in our model are theoretically grounded, but reciprocal or alternative causal relationships cannot be ruled out. Future research should employ longitudinal or quasi-experimental designs, for instance, by collecting multi-wave data across different stages of a course to temporally validate the proposed “awareness → reflection → production” sequence.

Furthermore, the scope of the model and the sample constitutes a boundary condition. Our intentional focus on the core cognitive-operational chain within a specific population—design students in higher education—was necessary for theoretical parsimony and to address a gap in the literature. However, this limits generalizability. Future studies could test the model's invariance across different populations (e.g., non-design students, senior practitioners) and educational contexts to examine whether path magnitudes differ. Moreover, our model deliberately excluded other significant variables for clarity. Future research can build upon our verified foundation by incorporating and testing additional mediators and moderators. For example, examining how factors such as individual motivational orientations (mastery vs. performance goals), information literacy, peer collaboration, or instructor feedback intensity interact with the core pathways we have identified would provide a more nuanced understanding of how to optimize AI integration in education.

8. Conclusions

This research, employing structural equation modeling, demonstrates that AI literacy impacts learning via a complex process, rather than through a straightforward progression from

knowledge to improved performance. The primary conclusion is a vital sequence of competencies: learning performance improves when students initially cultivate an understanding of AI's functions and limitations, subsequently engage in critical reflection, and ultimately demonstrate their practical skills. Meanwhile, ethical awareness plays a distinct role; its main significance resides in promoting academic well-being rather than explicitly enhancing performance. Therefore, educational practices and curricula in the AI era must adapt and develop accordingly. Resources should transition from solely tool-based training to a comprehensive approach that systematically fosters awareness, reflection, operational competencies, and ethical considerations. To foster a constructive learning environment, educators should establish equitable and reliable classroom standards and effectively demonstrate student progress through sequential outputs. This approach cultivates a positive feedback loop in which exemplary work and constructive learning experiences mutually enhance one another.

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