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GenAI-Assisted Design Education: Task Appraisals, Course-Value Reaffirmation, and Responsible Use

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Research Article

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Abstract

Generative artificial intelligence (GenAI) is increasingly embedded in design coursework, yet adoption measures reveal little about where students use it or how they interpret its implications for disciplinary learning. This study tested a task-anchored model linking GenAI appraisals, psychological responses, and design agency to course-value reaffirmation, generative-design learning engagement, and responsible-use behavioural intention. An anonymous survey of 303 design students in Chinese undergraduate and vocational or associate-degree institutions was analysed through partial least squares structural equation modelling (PLS-SEM), ten-factor confirmatory factor analysis (CFA), an orthogonal common method-factor model, predictive and competing-model assessment, and workflow-stage analysis. The model explained 43.7% of the variance in responsible-use behavioural intention. Course-value reaffirmation emerged as the core educational mechanism, strongly predicting learning engagement and responsible-use intention; engagement further predicted responsible-use intention. Triangulation showed that these downstream pathways and the design-agency effect were stable, whereas exploration- and anxiety-related routes were more method-sensitive. Among 210 respondents with complete task-stage records, GenAI use was concentrated in visual generation (64.8%) and ideation (46.2%). The findings indicate that GenAI's educational significance depends less on the breadth of workflow involvement than on whether students continue to recognise the value of disciplinary judgement, guided learning, professional agency, and accountable practice. Design curricula should therefore combine GenAI with structured comparison, critical evaluation, iterative revision, and explicit responsible-use standards.

1. Introduction

Generative artificial intelligence (GenAI) is becoming increasingly embedded in higher education, and design coursework gives it access to several distinct stages of practice. Students may use language models to interpret a brief, image generators to externalise alternatives, search-oriented systems to organise references, and editing tools to revise visual compositions. These forms of involvement place different demands on problem framing, comparison, critical evaluation, and the justification of design decisions. The central issue for design education is how students interpret GenAI while continuing to develop disciplinary judgement and responsibility for the final outcome.

Globally, policy on artificial intelligence in education is moving from general innovation advocacy towards institutional frameworks that combine human-centred development, rights protection, and accountable governance. UNESCO's Recommendation on the Ethics of Artificial Intelligence and its Guidance for Generative AI in Education and Research emphasise human dignity, human oversight, transparency, privacy, fairness, and the development of learners' capabilities (UNESCO, 2021, 2023). These developments indicate that the educational question is no longer simply whether artificial intelligence should be adopted, but how innovation can be balanced with learner rights, human judgement, and institutional responsibility.

China's policy environment reflects a parallel commitment to application and governance. The Education Powerhouse Construction Plan Outline (2024–2035) calls for artificial intelligence to support educational transformation, digital education, and the development of digital literacy among teachers and students (Central Committee of the Communist Party of China & State Council, 2025). The Opinions on Accelerating the Advancement of Education Digitalization further call for artificial-intelligence education across educational stages and for "general plus specialised" artificial-intelligence courses in universities (Ministry of Education et al., 2025). In 2026, the Action Plan for "AI plus Education" extended this agenda to talent development, teaching applications, innovation environments, and a secure governance ecosystem (Ministry of Education et al., 2026).

Together, these policies create a dual pressure for higher education. Universities are expected to use artificial intelligence to support teaching innovation, curriculum reform, and new approaches to talent development, while also ensuring that its use is transparent, secure, appropriate, and accountable. Design education must therefore neither exclude GenAI from the professional practices in which students will encounter it nor treat technological use as evidence of improved learning. Because generated material can enter ideation, visual expression, revision, and presentation, course quality increasingly depends on whether students can compare alternatives, identify the limits of generated content, explain the basis of their decisions, disclose AI involvement, and remain responsible for the final outcome.

This issue is particularly important because design education is not limited to producing visually persuasive outputs. Design learning involves framing problems, generating and comparing alternatives, responding to critique, revising decisions, and explaining why one solution is preferable to another (Cross, 2001; Norman, 2013; Schön, 1983).

GenAI may support this process by rapidly externalising ideas, expanding the visible solution space, and reducing barriers to experimentation. Structured classroom use has been associated with visualisation, exploration, motivation, and iterative development when students continue to interrogate, compare, and revise AI outputs (Abrusci et al., 2025; Chen et al., 2025; Wong et al., 2025). However, exposure to AI-generated images can also constrain the variety and originality of ideation when learners become anchored to initial examples (Wadinambiarachchi et al., 2024).

Additional hands-on work in architecture and design education, together with research on self-regulated learning, suggests that these benefits depend on how students direct and monitor AI-supported activity (Alamasi et al., 2026; Chiu, 2024).

Existing research leaves three gaps. First, much higher-education research examines acceptance, perceived usefulness, frequency of use, or continued-use intention through general technology-adoption measures (Kasneci et al., 2023; Labadze et al., 2023; Lo, 2023; Zawacki-Richter et al., 2019).

Recent student-perspective studies have documented perceived benefits, risks, and ambivalence surrounding GenAI use (Chan & Hu, 2023; Jensen et al., 2025; Johnston et al., 2024; Wu et al., 2025).

These studies sharpen understanding of student experience, but provide limited insight into where GenAI enters a design workflow and what students are trying to accomplish at each stage.

Related research on student AI competence and learning experiences likewise indicates that intended use is shaped by more than simple technology acceptance (Baidoo-Anu et al., 2024; Delcker et al., 2024).

Second, positive and negative responses are often examined separately even though the same task may feel enabling, uncertain, anxiety-provoking, and professionally threatening. A task-anchored perspective is needed to examine these responses as coexisting interpretations of one educational episode rather than as mutually exclusive attitudes toward technology.

Third, existing models rarely explain how these experiences reshape students' understanding of why formal design education remains necessary or distinguish continued learning effort from intentions to verify, revise, disclose, and document AI-supported work. The present study addresses this gap by treating course-value reaffirmation as an educational mechanism linking task-specific appraisals and psychological responses to learning engagement and responsible-use behavioural intention.

To address these limitations, the present study integrates cognitive appraisal and learner-agency perspectives. Appraisal theory explains how an event acquires emotional and behavioural significance through an individual's interpretation of its relevance, consequences, controllability, coping potential, and relation to the self (Folkman et al., 1986; Lazarus & Folkman, 1984; Scherer & Moors, 2019). Applied to GenAI-assisted design, this perspective distinguishes positive appraisal from uncertainty about output quality and concern that AI may simplify or displace formative design practice. These appraisals shape exploratory engagement, anxiety, and design-identity threat.

Learner agency provides a complementary perspective because agency is not equivalent to confidence in or acceptance of technology. It involves directing activity, evaluating alternatives, monitoring evidence, and retaining responsibility for decisions (Bandura, 2006; Wang et al., 2026; Yang et al., 2024).

The model positions course-value reaffirmation as the central educational response connecting these task-specific experiences to subsequent intentions. Course-value reaffirmation refers to students' renewed recognition that design coursework remains necessary for developing disciplinary judgement, evaluative criteria, professional standards, and accountable decision-making, even when GenAI accelerates the production of ideas or visual outputs. It is therefore distinct from general satisfaction with a course or perceived technological usefulness. A student may value the efficiency of GenAI while simultaneously recognising that formal instruction, critique, and disciplinary knowledge are still required to determine whether an output is appropriate, defensible, and professionally responsible. The study further distinguishes generative-design learning engagement from responsible-use behavioural intention. The former concerns students' willingness to continue investigating, comparing, and refining design solutions, whereas the latter concerns their intentions to verify AI outputs, modify them where necessary, disclose AI involvement, and retain records of the process.

The study also maps GenAI involvement across seven stages of respondents' most recent eligible design-course task. Task-stage location reveals how involvement is distributed across information organisation, ideation, visual generation, textual expression, revision, presentation, and evaluation, and permits comparison of localised and distributed integration patterns. This contextual layer distinguishes where GenAI enters the workflow from the educational quality and responsibility of its use.

Accordingly, this study addresses the following research questions:

RQ1: How do students' positive and threat-related appraisals of a recent GenAI-assisted design-course task shape exploratory engagement, AI-related anxiety, and design-identity threat?

RQ2: How do exploratory engagement, AI-related anxiety, design-identity threat, and design agency predict course-value reaffirmation, learning engagement, and responsible-use behavioural intention?

RQ3: Where does GenAI appear across the stages of a recent design-course task, and are there detectable differences in the specified associations between localised and distributed patterns of workflow involvement?

This study contributes by developing course-value reaffirmation as a task-specific educational mechanism, treating task-stage location and workflow breadth as a distinct contextual layer, and distinguishing continued learning engagement from responsible-use behavioural intention. Together, these contributions explain how a situated GenAI-assisted design episode acquires educational meaning and how that meaning may support professional judgement and accountable practice.

2. Literature review and theoretical framework

2.1 GenAI-assisted design learning: educational affordances and tensions

GenAI-assisted design learning differs from general educational technology adoption because design activity unfolds through a sequence of interdependent practices rather than a single decision to accept or use a tool. Students interpret briefs, organise references, externalise ideas, generate and compare alternatives, revise compositions, prepare presentations, and justify possible solutions. GenAI can participate in each of these activities, but its educational implications depend on the role it performs and on which forms of human judgement remain active (Cross, 2001; Gao et al., 2025; Ma et al., 2026; Norman, 2013; Schön, 1983).

Existing studies identify several potential educational affordances. GenAI can lower the threshold for externalising an initial idea, make alternative directions visible, and support rapid experimentation. These functions may be especially useful in early design stages, where tentative possibilities need to become available for comparison and critique. Classroom and field studies suggest that structured use can support visualisation, motivation, creative exploration, and iterative development when students continue

to interrogate and revise generated material (Abrusci et al., 2025; Chen et al., 2025; Lee & Kang, 2025; Wong et al., 2025).

However, increasing the speed or volume of output does not necessarily improve design learning. AI-generated examples may induce fixation when students anchor on visually persuasive outputs, and fluent results may encourage premature closure before adequate evaluative criteria have been developed (Abbas et al., 2024; Wadinambiarachchi et al., 2024). GenAI may therefore expand the apparent solution space while simultaneously weakening the reflective processes required to judge that space. Related work on cognitive offloading and learner agency indicates that reduced effort can function either as productive cognitive relief or as displacement of formative reasoning, depending on how the technology is incorporated into the task (Fan et al., 2026; Wang et al., 2026).

Evidence from experimental syntheses and broader educational analyses likewise cautions that GenAI availability does not by itself guarantee learning gains and may introduce new educational risks (Deng et al., 2025; Farrokhnia et al., 2024).

These tensions are consequential because design education is concerned not only with the production of artefacts but also with the development of disciplinary judgement, professional identity, and responsibility for decisions. Students must learn to explain why an alternative fits the brief, how evidence supports a choice, what revisions are necessary, and who remains accountable for the final design. GenAI may support these practices when it is treated as an object of comparison and revision, but it may displace them when polished output is treated as a substitute for inquiry, critique, or formative practice (Whitham et al., 2024; Yang & Shin, 2025).

Much of the higher-education literature nevertheless examines GenAI through general acceptance, perceived usefulness, frequency of use, or continued-use intention (Chan & Hu, 2023; Kasneci et al., 2023; Labadze et al., 2023; Lo, 2023; Zawacki-Richter et al., 2019). These measures are valuable for understanding adoption but provide limited insight into how students interpret a specific AI-assisted design episode. They do not distinguish uncertainty about the reliability of an output from concern that GenAI may simplify design training, nor do they explain whether students retain control over design decisions or reconsider why formal coursework remains necessary. A task-anchored framework is therefore needed to connect students' appraisals of GenAI with their psychological responses, design agency, educational reappraisal, and subsequent learning and responsible-use behavioural intentions.

2.2 Task-anchored appraisal of GenAI-assisted design

The theoretical unit of the present study is a recent, specific GenAI-assisted design-course task rather than a general attitude toward technology. Appraisal theory holds that an event becomes emotionally and behaviourally meaningful through an individual's interpretation of its relevance, consequences, controllability, coping potential, and relation to the self (Folkman et al., 1986; Lazarus & Folkman, 1984; Scherer & Moors, 2019). This perspective is well suited to GenAI because the same system can be

experienced differently according to the task brief, the student's prior knowledge, the quality of the output, and the perceived consequences of accepting or rejecting a suggestion.

The model distinguishes one opportunity appraisal from two forms of threat appraisal. Positive AI appraisal (PAA) captures the perception that GenAI helps a student begin, see alternatives, and progress through a design task. AI-output uncertainty perception (AUP) captures doubts about evidence, bias, reliability, and contextual fit. Concern about simplified design training (NAA) captures a disciplinary threat: the concern that sketching, experimentation, critique, and other formative practices may be displaced by the selection of polished generated results. The abbreviation NAA is retained throughout the manuscript for consistency with the established measurement model.

AUP and NAA are conceptually distinct. AUP concerns whether a particular output can be trusted or appropriately used in the focal task, whereas NAA concerns what repeated reliance on generated outputs may do to the formative structure of design education. A student may trust the general value of design training while remaining uncertain about a specific output; another may accept an output as plausible while worrying that using it too early reduces their own practice. The distinction therefore separates immediate output-level uncertainty from a broader concern about disciplinary learning.

The model also distinguishes psychological responses from a retained personal resource. AI-inspired exploration and positive emotion (AIE) represents curiosity, novelty, and willingness to try alternatives. AI-related anxiety (AIA) represents pressure, disrupted pace, and cognitive burden. Design-identity threat (DIT) concerns the student's developing role, competence, authorship, and professional value. Design agency (DA), by contrast, represents situated control: defining the problem, judging fit, explaining acceptance or rejection, and retaining responsibility for key decisions. Agency is therefore not equivalent to general confidence in or acceptance of AI; it concerns the student's capacity to direct and justify action within the focal design task (Bandura, 2006; Long & Magerko, 2020; Wang et al., 2026; Yang et al., 2024).

2.3 Opportunity and threat responses

When GenAI is appraised as an opportunity, students may perceive a larger solution space and a lower cost of initiating comparison. Early externalisation is valuable in design because ideas can be inspected, combined, rejected, or transformed (Cross, 2001; Schön, 1983). Studies of GenAI-supported design similarly report gains in visualisation, experimentation, and creative exploration when learners continue to compare and revise generated material (Abrusci et al., 2025; Chen et al., 2025; Wong et al., 2025). PAA should therefore be positively associated with AIE. This does not imply that perceived opportunity produces better design; it predicts only that students who see GenAI as enabling will report a more exploration-oriented positive experience in the focal task.

H1: Positive AI appraisal positively predicts AI-inspired exploration and positive emotion.

AUP represents uncertainty about the reliability and contextual fit of AI outputs. Research on trust and explainability suggests that uncertainty about how AI outputs are produced or whether they can be relied

upon can increase cognitive and evaluative burden (Glikson & Woolley, 2020; Shin, 2021). In educational settings, this burden may be experienced as anxiety when students must verify output quality within a time-limited task (Fan et al., 2026). AUP should therefore be positively associated with AIA.

H2: AI-output uncertainty perception positively predicts AI-related anxiety.

NAA concerns the educational process itself. If design training is reduced to selecting from generated outputs, students may worry that they are losing the practice through which professional judgement develops. This concern may create anxiety about whether they are learning adequately and may also threaten their developing identity as designers. This reasoning is consistent with research on design fixation, cognitive offloading, and learner agency, which shows that polished or readily available AI outputs can displace exploratory and formative activity when they are not critically interrogated (Wadinambiarachchi et al., 2024; Wang et al., 2026; Yang et al., 2024).

H3: Concern about simplified design training positively predicts AI-related anxiety.

AI-output uncertainty perception can also make authorship, competence, and the student's own contribution difficult to judge. When a system produces a fluent but opaque or weakly grounded result, uncertainty may be experienced not only as pressure but also as a challenge to the student's developing designer role. Agency theory helps explain why this uncertainty can unsettle perceived competence and authorship (Bandura, 2006). Recent work on AI in art and design education likewise identifies tensions around professional role and authorship (Whitham et al., 2024; Yang & Shin, 2025). We therefore distinguish the output-uncertainty pathway from the broader training-concern pathway.

H4: AI-output uncertainty perception positively predicts design-identity threat.

The training-concern pathway may also threaten design identity because it raises a question about whether the student is developing judgement or merely selecting outputs. This concern is distinct from uncertainty about one result because it implicates authorship, competence, and professional formation, which recent work identifies as central tensions in AI-assisted art and design education (Wadinambiarachchi et al., 2024; Whitham et al., 2024; Yang & Shin, 2025). NAA should therefore be positively associated with DIT.

H5: Concern about simplified design training positively predicts design-identity threat.

The distinction between AUP and NAA is central to the model. The two concerns may coexist, but they should not be reduced to a single generic fear of AI. Output uncertainty concerns the trustworthiness of a particular result, whereas training concern concerns what repeated reliance on generated outputs may do to formative design practice and professional identity. This distinction is consistent with recent work on design pedagogy, cognitive offloading, and agency-supportive or agency-eroding use (Fan et al., 2026; Wang et al., 2026; Whitham et al., 2024; Yang & Shin, 2025).

2.4 Design agency and course-value reaffirmation

Course-value reaffirmation (DCVP) is the focal educational reappraisal construct. It refers to students' renewed recognition, after a GenAI-assisted task, that design coursework remains necessary for developing disciplinary judgement, evaluative criteria, professional standards, and accountable decision-making. DCVP is not general course satisfaction or perceived technological usefulness. A student may value GenAI's efficiency while simultaneously recognising that formal instruction, critique, and disciplinary knowledge remain necessary to determine whether an output is appropriate, defensible, and professionally responsible.

AIE is expected to be positively associated with DCVP because exploration can make disciplinary criteria more visible. Comparing multiple AI-generated alternatives may reveal that a larger solution space still requires principles for judging relevance, coherence, feasibility, and fit. Classroom and field studies support this reasoning by showing that GenAI can support creative exploration and iterative learning when generated material remains an object of comparison and revision (Abrusci et al., 2025; Chen et al., 2025; Wong et al., 2025). However, exploration is not assumed to be educationally beneficial by itself; it may remain superficial when students generate multiple outputs without reflective comparison.

H6: AI-inspired exploration and positive emotion positively predict course-value reaffirmation.

DA represents the coping and control resource that allows students to integrate AI without surrendering judgement. Students who define the problem, evaluate fit, and explain why they accept, modify, or reject an output should be better positioned to recognise the continuing value of design education. Agency makes the boundary between generation and judgement visible and should therefore support DCVP (Amershi et al., 2019; Shin, 2021; Shneiderman, 2020).

H7: Design agency positively predicts course-value reaffirmation.

AIA may have competing educational implications. Anxiety may prompt students to recognise the need for disciplinary guidance when uncertainty becomes difficult to manage, but it may also consume cognitive resources and reduce constructive engagement. Appraisal theory permits this ambivalent pathway because a stressful appraisal can signal that coping resources or guidance are needed, while still carrying the possibility of impairment (Folkman et al., 1986; Lazarus & Folkman, 1984). Recent reviews of student responses to GenAI similarly describe anxiety and ambivalence as context-dependent rather than uniformly negative (Jensen et al., 2025; Wu et al., 2025). The present study tests the positive reappraisal possibility as a qualified directional hypothesis rather than assuming that anxiety is inherently educationally beneficial.

H8: AI-related anxiety positively predicts course-value reaffirmation.

DIT is not expected to be educationally beneficial in itself. However, a task that challenges what counts as the student's own design ability may trigger compensatory educational reappraisal and make the role of formal design education more salient. This possibility follows from agency and identity perspectives: a challenge to perceived competence may make the social and educational conditions of competent

action more visible (Bandura, 2006; Yang et al., 2024). Design-education scholarship likewise argues that GenAI makes the purposes of critique, authorship, and professional formation more explicit (Whitham et al., 2024; Yang & Shin, 2025). A positive association would indicate recognition of course value in response to a threatened professional self; it would not indicate improved well-being, identity security, or design competence.

H9: Design-identity threat positively predicts course-value reaffirmation.

2.5 Learning engagement and responsible-use behavioural intention

DCVP is proposed to connect the immediate GenAI episode to two distinct downstream orientations. Generative-design learning engagement (GDLE) concerns students' willingness to continue investigating, comparing, discussing, and refining design solutions. Responsible-use behavioural intention (RAUB) concerns intentions to check errors, screen and modify AI results, explain AI's role, and retain prompts or modification records. GDLE therefore concerns continued educational effort, whereas RAUB concerns intended verification, transparency, and accountability.

When students recognise why design coursework remains necessary, they may be more willing to continue improving an AI-assisted proposal rather than treating the first fluent output as complete. This argument follows from reflective design-learning accounts in which the value of coursework lies in framing, comparison, critique, and revision rather than output production alone (Cross, 2001; Schön, 1983). Recent design-education studies further suggest that GenAI supports learning when students use generated material as an object of interrogation and development rather than as a finished answer (Abrusci et al., 2025; Wong et al., 2025). DCVP should therefore be positively associated with GDLE.

H10: Course-value reaffirmation positively predicts generative-design learning engagement.

Continued learning engagement may also support responsible-use behavioural intention because students who compare sources, test alternatives, and refine a solution are more likely to recognise the need to verify and document AI-supported work. Research on AI policy education and academic integrity similarly emphasises human judgement, disclosure, and accountability as practices that should accompany AI-supported learning (Chan, 2023; Cotton et al., 2024; UNESCO, 2023). This pathway distinguishes active learning continuation from passive intention to use AI.

H11: Generative-design learning engagement positively predicts responsible-use behavioural intention.

DCVP should also have a direct association with RAUB. Recognition of the course's continuing role may reinforce the idea that students remain answerable for the final design and that AI involvement should be transparent, revisable, and supported by evidence (Chan, 2023; Cotton et al., 2024; UNESCO, 2023). The model retains this direct path alongside the GDLE pathway because educational reappraisal may support responsibility even when it does not first increase continued engagement.

H12: Course-value reaffirmation positively predicts responsible-use behavioural intention.

2.6 Workflow location as a contextual descriptor

GenAI involvement can occur at different stages of design work, including reference search and information organisation, idea generation, visual generation, textual expression, revision, presentation, and evaluation of alternatives. These stages involve different cognitive and disciplinary demands, making workflow location useful contextual information (Gao et al., 2025; Hutchins, 1995; Ma et al., 2026; Orlikowski, 2000; Wong et al., 2025).

Workflow breadth captures the distribution of GenAI involvement across the design process and therefore adds information that general-use measures cannot provide. Broad coverage may represent extensive experimentation or extensive delegation, whereas concentrated use may reflect a deliberately bounded application. Treating workflow breadth as an observed contextual dimension makes it possible to examine how the location and distribution of GenAI use relate to the psychological model while preserving the conceptual distinction between technological involvement, learning quality, agency, and responsibility.

The study records GenAI involvement across seven stages of respondents' most recent eligible design-course task and tests whether the proposed structural effects differ between localised and distributed patterns of workflow involvement. This task-breadth comparison functions as a boundary-condition analysis alongside the latent psychological model. The operational definition, grouping rule, statistical power, and measurement-invariance procedure are reported in the Method section.

2.7 Conceptual integration and research model

Taken together, the model treats PAA, AUP, and NAA as task appraisals that activate AIE, AIA, and DIT, while DA represents the student's retained capacity to direct and justify design decisions. These antecedents converge on DCVP, which transmits the task experience to GDLE and RAUB. Workflow breadth remains an observed contextual condition rather than part of the latent psychological sequence.

The proposed model and H1–H12 are summarised in Fig. 1; the workflow-breadth grouping is defined operationally in the Method section.

3. Methodology

GenAI-assisted design learning is a situated process rather than a single technology-acceptance decision. In a recent design-course task, the same system may help students initiate ideas, expand possible directions, and accelerate expression, while also creating uncertainty about output reliability, disrupting the development of design competence, or prompting reflection on the continuing value of formal design education. These responses cannot be adequately understood through decontextualised questions about whether students generally use AI. The present study therefore anchored all substantive responses to one recent eligible design-course task and followed a linked research process involving

contextualised construct development, expert review, bilingual translation, pilot testing, and a cross-sectional survey of design students. This design enabled the study to examine how task appraisals and psychological responses were associated with design agency, course-value reaffirmation, learning engagement, and responsible-use intention, while task-stage breadth was retained as an observed description of where GenAI entered the design workflow.

3.1 Research design and ethical approval

This study employed a cross-sectional, task-anchored quantitative survey to examine students' interpretations of a recent GenAI-assisted design-course task. Rather than asking about GenAI use in general, respondents answered with reference to their most recent eligible task completed within the preceding three months. This task anchor placed appraisal, psychological-response, agency, course-value, engagement, and responsible-use measures within a common educational episode.

The study received formal ethical approval from the Biomedical Ethics Committee of Henan Finance University (Ethics Approval No. 2026-006; project title: Psychological Experience Profiles and Responsible Generative AI Learning Among Design Students in Higher Education). The approved project was classified as minimal-risk social-science research involving adult participants. The present manuscript reports the anonymous online questionnaire component of the approved project. The questionnaire did not target minors or vulnerable populations and did not involve biological samples, medical testing, pharmaceutical intervention, invasive procedures, or high-risk behavioural manipulation. No sensitive personal information was collected in the questionnaire dataset. Participation was voluntary, and informed consent was obtained before questionnaire completion. Participants were informed of the study purpose, the voluntary nature of participation, confidentiality protections, and their right to discontinue participation without penalty. All procedures followed the approved protocol and applicable national and international ethical requirements, including the principles of the Declaration of Helsinki.

3.2 Participants, recruitment, and analytical samples

The sampling strategy was designed to reach students with recent first-hand experience of GenAI use in design coursework. Eligibility therefore required respondents to be at least 18 years old, enrolled in a design-related programme, and able to identify a design-course task involving GenAI within the preceding three months. This criterion ensured that responses referred to a concrete educational episode rather than to general attitudes towards artificial intelligence. A convenience-sampling strategy was used. The questionnaire was hosted on Wenjuanxing and circulated to students enrolled in design-related programmes at undergraduate universities and higher vocational or associate-degree colleges in China. Recruitment was open to students from any design-related major. Because the survey link was distributed without a fixed invitation list or capped sampling frame, the number of students who received the invitation and a conventional response rate could not be determined. The platform was configured to permit only one submission from each respondent. Data were collected from 18 to 22 June 2026.

A total of 309 questionnaires were submitted. Six respondents failed the prespecified instructed-response item, which instructed them to select ‘mostly agree’, and were excluded. The primary analytical sample therefore comprised 303 respondents. All retained respondents completed the 40 substantive reflective items, so no missing-value imputation was required for the primary model.

Among the 303 eligible respondents, 163 were coded as men, 139 as women, and one selected another or a non-disclosure option. Ages ranged from 19 to 24 years (M = 21.27, SD = 1.11). The separate task-stage module was completed by 210 respondents. Respondents with and without complete task-stage records did not differ materially in the ten substantive construct scores (absolute Cohen’s $d \leq .160$; all $p \geq .194$), although their school-type composition differed (Cramer’s $V = .251$, $p < .001$). The task-stage subgroup analyses were therefore treated as exploratory and did not determine inclusion in the primary structural model.

3.3 Instrument adaptation, translation, pilot testing, and data collection

The questionnaire was developed through four linked steps. First, measurement items were adapted from established scales and relevant prior studies to reflect GenAI use within design coursework and the task-anchored context of the present study. Second, four university faculty members in design disciplines reviewed the draft questionnaire for conceptual relevance, clarity, contextual appropriateness, and construct coverage. Their recommendations were incorporated before pilot testing.

Third, the questionnaire was administered in Chinese. Items originally developed in English were translated using an independent forward–back translation procedure conducted by bilingual researchers. Discrepancies between the original, translated, and back-translated versions were discussed and resolved by consensus to preserve semantic equivalence and alignment with the intended construct definitions.

Fourth, the revised questionnaire was pilot-tested with 20 design students who were not included in the main sample (10 women and 10 men). The pilot test examined item clarity, comprehensibility, response burden, contextual appropriateness, and construct coverage. The combined expert-review and pilot-testing process resulted in the removal of three open-ended questions, the removal of four scale items that were unsuitable for the design-education context or insufficiently aligned with the intended constructs, and wording revisions to six items. The final instrument contained 40 core construct items. All core items were mandatory and had to be completed before questionnaire submission. The final Chinese wording and English reporting translations are provided in Online Resource 1, Table S1.

Several procedural measures were incorporated during questionnaire administration to reduce potential common method bias. The survey was anonymous and voluntary, and no directly identifying information was requested. Participants were informed that there were no right or wrong answers and that their responses would be used only for academic research. Items were organised into conceptually distinct theory-based sections, and appraisal, psychological-response, agency, course-value, engagement, and

responsible-use items were presented in separate blocks. Wording was reviewed to avoid unnecessary semantic overlap between adjacent items while preserving the common task anchor. These procedural controls complemented the subsequent statistical assessment of common method variance.

3.4 Measures and operationalization

Ten reflective constructs operationalised the four conceptual layers identified above: task appraisals (PAA, AUP, and NAA), psychological responses and personal resources (AIE, AIA, DIT, and DA), educational reappraisal (DCVP), and downstream outcomes (GDLE and RAUB). Each construct comprised four items rated from 1 (strongly disagree) to 7 (strongly agree). Table 1 summarises construct roles and operational meanings; Online Resource 1, Table S1 provides the construct codebook and final item wording.

Table 1
Construct operationalisation

Code	Role in model	Operational meaning	Illustrative item focus	Source logic
PAA	Exogenous appraisal	Perceived enabling value of GenAI in the focal task	Faster initiation; unexpected directions; smoother progress	Appraisal and human-AI support
AUP	Exogenous appraisal	Uncertainty about reliability, bias, evidence, and task fit	Need to verify; possible error; unclear limitations	Trust, explainability, AI literacy
DA	Exogenous resource	Retained control over framing, evaluation, acceptance, and final decisions	Define the problem; explain adoption or rejection	Human agency and human-centered AI
AIE	Parallel response	Exploration, novelty, curiosity, and positive momentum	Willingness to try alternatives; freshness of process	Creativity support and design practice
AIA	Parallel response	Pressure, disrupted rhythm, and cognitive burden	Too much output; tension when AI appears complete	AI anxiety and ambivalence
NAA	Exogenous threat appraisal	Concern that AI bypasses formative design training	Skipping reasoning, sketching, testing, or critique	Cognitive offloading and design pedagogy
DIT	Parallel response	Threat to developing competence, authorship, and designer role	Unclear personal capability; role challenged	Identity threat and professional formation
DCVP	Central mediator	Reaffirmed value of disciplinary education after the task	Standards and judgment remain necessary	Educational reappraisal
GDLE	Serial mediator	Willingness to continue refining, verifying, and discussing the design	Continue from “usable” to “better”; reflect on choices	Engagement and self-regulated learning
RAUB	Final outcome	Intention to check, modify, explain, and retain AI-use evidence	Error checking; disclosure; prompts and modification records	Responsible AI and academic integrity

Note. Construct abbreviations are defined in the first column; each construct was measured reflectively with four items.

Task-stage involvement was measured separately from the reflective constructs. Respondents indicated whether GenAI had participated in seven non-interchangeable stages of their focal task: information organisation, ideation, visual generation, textual expression, revision, presentation, and evaluation. Task breadth was calculated as the sum of seven binary workflow-stage indicators. Respondents reporting GenAI use in one or two stages were classified as the localised-integration group (n = 83), whereas those

reporting use in three or more stages were classified as the distributed-integration group (n = 127). This observed coverage index characterised the distribution of GenAI involvement and defined the comparison groups. Modelling task breadth as an observed contextual variable preserved its role as a workflow descriptor and boundary condition alongside the latent psychological process.

3.5 Data analysis

The analysis followed the logic of the research design. SPSS 26 was used for descriptive statistics and preliminary screening, whereas SmartPLS 4 was used for measurement and structural assessment. First, the measurement model was examined through item loadings, internal consistency, composite reliability, AVE, cross-loadings, the Fornell–Larcker criterion, HTMT, and ten-factor CFA. Second, PLS-SEM was used to test the hypothesised paths, explained variance, effect sizes, collinearity, and bootstrapped indirect effects. Third, common-method sensitivity, PLSpredict, CVPAT, competing models, task-stage distributions, MICOM, and permutation-based group comparisons were used to examine the stability, predictive boundary, and workflow context of the proposed mechanism. Coefficients are interpreted as theory-consistent associations within a cross-sectional model rather than temporal causal estimates. The choice of PLS-SEM followed established guidance for theory-oriented models with latent composites and a prediction-oriented supplement (Hair et al., 2019, 2022; Rigdon, 2012).

Measurement assessment combined standardised item loadings, Cronbach's α, composite reliability (ρc), average variance extracted (AVE), cross-loadings, the Fornell–Larcker criterion, and the heterotrait–monotrait ratio (HTMT; Henseler et al., 2015) to evaluate indicator reliability, internal consistency, convergent validity, and discriminant validity. Structural assessment included path coefficients, 95% percentile bootstrap confidence intervals from 5,000 case resamples, coefficients of determination (R^2), effect sizes (f^2), predictor variance inflation factors (VIFs), and bootstrapped indirect effects. Each resample re-estimated both the outer and structural models. Composite reliability and the structural estimates were interpreted in line with guidance on consistent partial least squares path modelling (Dijkstra & Henseler, 2015).

Predictive performance was assessed with SmartPLS 4 repeated ten-fold PLSpredict using 10 repetitions for all 24 indicators of the six endogenous constructs (Shmueli et al., 2019). The PLSpredict/CVPAT analysis used a fixed random seed so that the repeated cross-validation splits were reproducible. The PLS-SEM structural model was estimated with path weighting. PLS predictions were compared with SmartPLS's indicator-average (IA) and linear-model (LM) benchmarks, and paired loss differences were evaluated with the cross-validated predictive ability test (CVPAT). The LM comparison is the software-defined linear benchmark rather than an earliest-antecedent benchmark; negative differences indicate lower PLS prediction loss than the benchmark. The paired predictive-loss comparison follows the logic of cross-validated predictive ability testing (Liengaard et al., 2021).

Common method variance was evaluated as a dedicated validation layer within the methodological triangulation strategy (Kock et al., 2021; MacKenzie et al., 2011; Podsakoff et al., 2003; Williams et al., 2010). Harman's unrotated single-factor screen served as an initial diagnostic. A candidate marker

variable was examined, but its correlations with the substantive constructs made it unsuitable as a clean method marker. We therefore estimated an orthogonal common latent method-factor model as a sensitivity analysis, with each item loading on its intended trait and on one orthogonal common factor. Maximum-likelihood fit was evaluated using chi-square, CFI, TLI, RMSEA, SRMR, AIC, and BIC. We used the method-factor estimates to identify paths that remained stable across measurement specifications and paths whose magnitudes depended on the specification. This sensitivity analysis complements the primary PLS-SEM evidence.

For the workflow-breadth comparison, measurement invariance and path differences were assessed using MICOM and permutation-based multigroup analysis with 5,000 permutations (Henseler et al., 2016). The localised (n = 83) and distributed (n = 127) groups provided an approximate minimum detectable standardised path difference of .385 at 80% power and two-sided alpha = .05, increasing to approximately .510 after a conservative Bonferroni adjustment for 12 contrasts. This power boundary informed interpretation of the group effects. The de-identified model dataset and analysis files are retained by the authors and are available upon reasonable request, subject to the stated data-governance restrictions.

4. Results

4.1 Descriptive statistics and construct correlations

Across the 303-case structural sample, construct means ranged from 4.69 to 5.11 on the seven-point response scale, with standard deviations between 1.03 and 1.11. Course-value reaffirmation had the highest mean (M = 5.11, SD = 1.04), followed by AI-output uncertainty perception and design agency (both M = 5.02). Responsible-use behavioural intention averaged 4.69 (SD = 1.09). Skewness ranged from − .30 to .07 and kurtosis from − .63 to − .09, indicating well-distributed responses without pronounced floor or ceiling effects.

All pairwise construct correlations were positive and statistically significant (r = .521–.673, p < .001). The strongest association was between DCVP and GDLE (r = .673), followed by NAA and DIT (r = .666) and AIE and NAA (r = .660). DCVP was also strongly related to DA (r = .638) and RAUB (r = .633). These patterns show substantial theoretical covariance across the appraisal, identity, agency, and educational outcome layers while remaining below levels that would indicate construct redundancy.

4.2 Measurement model and ten-factor confirmation

The PLS measurement model demonstrated strong internal consistency and convergent validity. Across the ten reflective constructs, Cronbach's alpha ranged from .880 to .906, composite reliability (rho_c) from .917 to .934, and AVE from .735 to .779. All item loadings exceeded .80, with a minimum of .824. Because rho_A was not separately estimated, Table 2 reports rho_c as the composite-reliability coefficient.

Table 2
Reflective measurement-model results

Construct	Items	Min loading	Max loading	α	ρc	AVE
PAA	4	0.877	0.891	0.906	0.934	0.779
AUP	4	0.824	0.895	0.892	0.925	0.756
NAA	4	0.833	0.890	0.891	0.924	0.753
DA	4	0.845	0.895	0.897	0.928	0.764
AIE	4	0.850	0.897	0.895	0.927	0.761
AIA	4	0.876	0.890	0.903	0.932	0.774
DIT	4	0.846	0.866	0.880	0.917	0.735
DCVP	4	0.864	0.882	0.898	0.929	0.766
GDLE	4	0.853	0.883	0.895	0.927	0.761
RAUB	4	0.834	0.901	0.898	0.929	0.766

Note. α = Cronbach's alpha; ρc = composite reliability; AVE = average variance extracted.

Discriminant validity was also established. HTMT values ranged from .580 to .753, remaining below the conservative .85 threshold. The largest value occurred between NAA and DIT (.753), followed by DCVP and GDLE (.750). These pairs are theoretically adjacent yet empirically distinct: NAA concerns the possible simplification of formative design training, whereas DIT concerns the student's professional role and identity; DCVP concerns renewed recognition of the value of design education, whereas GDLE concerns continued effort to investigate, compare, and improve the design. Selected discriminant-validity evidence is reported in Table 3.

Table 3
Discriminant-validity and ten-factor CFA evidence

Check	Result	Interpretation
HTMT range	0.580–0.753	Below .85 for all pairs
Largest HTMT	NAA-DIT = .753	Adjacent but empirically distinguishable
Loading range	0.824–0.901	All items above .80
Alpha range	0.880–0.906	High internal consistency
Composite reliability range	0.917–0.934	Composite reliability supported
AVE range	0.735–0.779	Convergent validity supported
Ten-factor CFA	CFI = 0.993; TLI = 0.993; RMSEA = 0.017; SRMR = 0.029	Good correlated-trait measurement fit

Note. HTMT = heterotrait–monotrait ratio; CFA = confirmatory factor analysis; CFI = comparative fit index; TLI = Tucker–Lewis index; RMSEA = root mean square error of approximation; SRMR = standardised root mean square residual.

The correlated ten-factor CFA independently confirmed the proposed measurement structure and showed excellent fit: chi-square(695) = 754.57, CFI = 0.993, TLI = 0.993, RMSEA = 0.017, and SRMR = 0.029. Together, the PLS assessment and CFA established reliable measurement, convergent validity, and empirical distinctiveness across the ten constructs. The CFA software export of the ten-factor measurement structure is presented in Fig. 2.

4.3 Structural model and hypothesis testing

The primary PLS-SEM explained 42.1% of the variance in AIE, 46.1% in AIA, 48.1% in DIT, 56.0% in DCVP, 45.5% in GDLE, and 43.7% in RAUB. These moderate-to-substantial R^2 values demonstrate strong explanatory capacity across the appraisal-response-course-value sequence and establish course-value reaffirmation as the central educational mechanism connecting the GenAI-assisted task with learning engagement and responsible-use behavioural intention. The explained-variance results are summarised in Table 4.

Table 4
Explained variance of endogenous constructs

Construct	R^2	Adjusted R^2
AIE	0.421	0.419
AIA	0.461	0.457
DIT	0.481	0.478
DCVP	0.560	0.554
GDLE	0.455	0.453
RAUB	0.437	0.433

Note. R^2 = coefficient of determination.

The 5,000-resample bootstrap supported all twelve prespecified direct effects. DCVP was the strongest proximal predictor of GDLE (β = .674) and a major predictor of RAUB (β = .462), while GDLE also predicted RAUB (β = .254). Among the upstream paths, PAA strongly predicted AIE (β = .648), and NAA strongly predicted DIT (β = .532). The results therefore place course-value reaffirmation at the centre of the model: students who more strongly recognised the continuing value of disciplinary judgement, professional standards, and accountable decision-making showed greater learning engagement and stronger responsible-use behavioural intention. Detailed bootstrap estimates are reported in Table 5. The structural model path estimates and hypothesis-support pattern are summarised in Fig. 3.

Table 5
Direct structural effects in the primary sample

Hyp.	From	To	β	2.5% CI	97.5% CI	p
H1	PAA	AIE	0.649	0.577	0.716	< .001
H2	AUP	AIA	0.238	0.123	0.365	< .001
H3	NAA	AIA	0.508	0.380	0.618	< .001
H4	AUP	DIT	0.226	0.120	0.337	< .001
H5	NAA	DIT	0.533	0.429	0.631	< .001
H6	AIE	DCVP	0.265	0.146	0.379	< .001
H7	DA	DCVP	0.283	0.186	0.378	< .001
H8	AIA	DCVP	0.132	0.031	0.234	0.010
H9	DIT	DCVP	0.212	0.109	0.317	< .001
H10	DCVP	GDLE	0.674	0.613	0.732	< .001
H11	GDLE	RAUB	0.254	0.137	0.371	< .001
H12	DCVP	RAUB	0.462	0.344	0.576	< .001

Note. n = 303. β = standardised path coefficient; CI = percentile bootstrap confidence interval. Confidence intervals and p values are based on 5,000 resamples with full re-estimation of the measurement and structural models.

Effect-size diagnostics reinforced this pattern. Large effects were observed for PAA → AIE, NAA → DIT, and DCVP → GDLE; medium effects were observed for NAA → AIA and DCVP → RAUB; and the remaining effects were small but statistically supported. The largest structural VIF was 2.083 for DIT in the DCVP equation, and all predictor VIFs were below 2.10, indicating that the estimated effects were not distorted by problematic collinearity. Corresponding effect sizes and predictor VIFs are reported in Table 6.

Table 6
Effect sizes and predictor collinearity diagnostics

Hyp.	Path	f^2	Magnitude	VIF
H1	PAA → AIE	0.727	large	1.000
H2	AUP → AIA	0.067	small	1.573
H3	NAA → AIA	0.304	medium	1.573
H4	AUP → DIT	0.063	small	1.573
H5	NAA → DIT	0.348	medium	1.573
H6	AIE → DCVP	0.077	small	2.061
H7	DA → DCVP	0.099	small	1.840
H8	AIA → DCVP	0.021	small	1.847
H9	DIT → DCVP	0.049	small	2.083
H10	DCVP → GDLE	0.834	large	1.000
H11	GDLE → RAUB	0.063	small	1.834
H12	DCVP → RAUB	0.207	medium	1.834

Note. f^2 = effect size; VIF = variance inflation factor. Magnitudes are interpreted using conventional PLS-SEM thresholds.

4.4 Indirect effects and the course-value reaffirmation mechanism

The indirect-effect analysis further established course-value reaffirmation as the principal transmission mechanism in the model. DCVP predicted RAUB sequentially through GDLE (β = .171, 95% CI [.092, .253]), showing that renewed recognition of course value is associated with responsible-use readiness partly through continued commitment to improve the design. PAA also predicted RAUB through AIE and DCVP (β = .079, 95% CI [.042, .122]), while DIT predicted RAUB through DCVP (β = .098, 95% CI [.045, .160]). Additional chains from AUP and NAA through anxiety or identity threat were positive but smaller. Collectively, these effects show how a GenAI-assisted design episode is converted from an immediate psychological experience into educational reappraisal, continued engagement, and responsible-use behavioural intention.

4.5 Methodological triangulation and refinement of the structural mechanism

The unrotated principal-component screen placed 49.45% of total item variance in the first component. Correlations between the candidate marker variable and the substantive constructs ranged from .508 to .677, so the variable was not a clean method marker. The orthogonal common method-factor model

fitted well: chi-square(655) = 678.07, CFI = .997, TLI = .997, RMSEA = .011, and SRMR = .026. The common factor accounted for 7.32% of item variance on average (median = 3.89%; range = 0.01%–24.23%). Because the marker was substantively related to the focal constructs, these estimates are reported as a sensitivity analysis rather than as a direct correction for common method bias. AIC and BIC favoured the more parsimonious ten-factor model. The model-fit and method-variance summary is reported in Online Resource 1, Table S9.

Methodological triangulation refined rather than displaced the structural interpretation. DCVP → GDLE (.750 to .717), DCVP → RAUB (.532 to .549), GDLE → RAUB (.224 to .213), and DA → DCVP (.305 to .336) remained stable. DIT → DCVP increased from .228 to .452, preserving direction while showing sensitivity in magnitude. By contrast, AIE → DCVP weakened from .281 to .114, and AIA → DCVP changed from .107 to − .052, identifying exploration and anxiety as method-sensitive antecedents. Table 7 and Online Resource 1, Table S10 summarise the focal comparison.

Table 7
Comparison of focal paths across CFA specifications

Path	Ten-factor CFA β	CFA + method factor β	Δβ	Triangulated interpretation
DA → DCVP	.305	.336	+ .031	Stable
DIT → DCVP	.228	.452	+ .224	Direction reinforced; magnitude-sensitive
DCVP → GDLE	.750	.717	− .034	Highly stable
DCVP → RAUB	.532	.549	+ .017	Highly stable
GDLE → RAUB	.224	.213	− .011	Highly stable
AIE → DCVP	.281	.114	− .167	Magnitude-sensitive
AIA → DCVP	.107	− .052	− .159	Direction-sensitive

Note. β values were derived from the latent-trait correlation matrices of the ten-factor CFA and the CFA with an orthogonal common method factor; Δβ = method-factor coefficient minus ten-factor coefficient.

4.6 Predictive assessment and competing models

All 24 endogenous indicators showed positive Q^2predict values, ranging from .272 to .429, with a mean of .337. PLS-SEM RMSE was lower than the indicator-average benchmark for all 24 indicators and lower than the SmartPLS linear-model benchmark for 7 indicators. CVPAT showed a clear PLS advantage over the indicator-average benchmark (PLS loss = .990 vs. 1.493, Δ = −.503, t = 10.812, p < .001), but the overall comparison with the linear-model benchmark slightly favoured the linear benchmark (PLS loss = .990 vs. .954, Δ = +.036, t = 2.483, p = .014). At the construct level, PLS performed significantly better for

course-value reaffirmation; the linear benchmark had lower loss for AI-inspired exploration and positive emotion and for generative-design learning engagement. The differences were not significant for AI-related anxiety, design-identity threat, or responsible-use behavioural intention. Construct-level results are reported in Table 8 and the paired loss comparisons in Table 10.

Table 8
Repeated PLSpredict results for endogenous constructs

Target	Mean Q^2predict	PLS RMSE	IA RMSE	LM RMSE	PLS < IA	PLS < LM
AIE	0.417	0.999	1.208	0.936	4/4	0/4
AIA	0.450	1.013	1.254	1.017	4/4	2/4
DIT	0.472	0.999	1.234	0.988	4/4	1/4
DCVP	0.518	0.928	1.195	0.954	4/4	4/4
GDLE	0.418	0.980	1.186	0.944	4/4	2/4
RAUB	0.394	1.046	1.252	1.014	4/4	1/4
Overall	0.337	0.994	1.221	0.975	24/24	7/24

Note. Q^2predict = cross-validated predictive relevance; PLS = partial least squares; RMSE = root mean square error; IA = indicator-average benchmark; LM = SmartPLS linear-model benchmark.

The competing-model rows provide structural robustness comparisons. The direct appraisal extension explained more variance in RAUB, whereas the serial model remained the theory-specified reference structure. Its alternative prediction-loss entries came from auxiliary 303-case structural-comparison runs and are therefore descriptive; formal CVPAT results for the current SmartPLS 4 export appear in Table 10. The serial structure was retained for theoretical parsimony and coherence with the hypothesised educational sequence. Competing-model results are summarised in Table 9.

Table 9
Competing-model comparison

Model	RAUB R^2	Adjusted R^2	Mean Q^2predict	Mean PLS prediction loss	Interpretation
Proposed serial model	0.437	0.433	.337	.990	Reference model; predictive relevance confirmed
Full mediation: no DCVP → RAUB	0.320	0.318	0.335	0.996	Higher mean loss than proposed (.996 vs .990; difference = + .006)
Direct appraisal extension	0.543	0.533	0.349	0.974	Lower mean loss than proposed (.974 vs .990; difference = − .016)
Reverse order: GDLE → DCVP	0.437	0.434	0.351	0.982	Lower mean loss than proposed (.982 vs .990; difference = − .008)
Parallel DCVP/GDLE predictors	0.438	0.434	0.351	0.982	Lower mean loss than proposed (.982 vs .990; difference = − .008)

Note. R^2 = coefficient of determination; Q^2predict = cross-validated predictive relevance. The proposed-model row uses the current SmartPLS 4 PLSpredict export. Alternative-model prediction-loss entries are auxiliary 303-case structural-comparison results and are shown descriptively; formal benchmark inference is reported in Table 10.

Table 10
Paired cross-validated prediction-loss comparisons

Comparison	Mean PLS prediction loss	Benchmark loss	Δ	t	p (PLS better)	Conclusion
PLS vs indicator-average benchmark	.990	1.493	−.503	10.812	< .001	PLS significantly lower loss
PLS vs SmartPLS linear-model benchmark	.990	.954	+ .036	2.483	.014	LM lower overall loss

Note. Δ = PLS loss minus benchmark loss; negative values favour PLS. The comparisons are the formal CVPAT results from the current SmartPLS 4 PLSpredict export.

4.7 GenAI workflow distribution and boundary-condition analysis

Among the 210 respondents with complete task-stage records, GenAI participated in an average of 2.75 stages (SD = 1.11), with a median of three and a range from one to six. Eighty-three respondents were

classified as localised integration and 127 as distributed integration. The distribution confirms that GenAI involvement was structurally uneven rather than uniformly spread across the design workflow.

Visual-reference generation was the most common stage (64.8%), followed by idea generation (46.2%), revision and evaluation/comparison (40.0% each), copy or proposal expression (32.4%), reference search (31.4%), and presentation materials (20.0%). This pattern positions GenAI primarily as a generative and externalising resource: students used it most intensively to produce and visualise possibilities, while the distinct disciplinary work of evaluating, revising, and defending those possibilities remained a separate educational demand. Percentages are based on the 210 complete task-stage records. Table 11 and Fig. 4 summarise this distribution.

Table 11
GenAI participation across design-task stages (n = 210)

Task stage	**n**	**%**
Reference search / information organization	66	31.4
Idea generation / design direction	97	46.2
Image, sketch, effect, or visual-reference generation	136	64.8
Copy, explanation, or proposal expression	68	32.4
Layout, color, composition, or detail revision	84	40.0
Presentation board, slide, or reporting material	42	20.0
Evaluation, optimization, or comparison of alternatives	84	40.0

Note. Respondents could select multiple stages; percentages therefore do not sum to 100%. Percentages are based on the 210 complete task-stage records.

Before comparing structural paths, the 5,000-permutation MICOM procedure supported full measurement invariance for nine of the ten composites. AIA narrowly failed the Step 2 compositional-invariance criterion (c = .9985, 5% quantile = .9988, p = .022); comparisons involving AIA were therefore interpreted cautiously. The remaining constructs showed no evidence against equality of composite means or variances. The MICOM permutation results are reported in Table 12.

Table 12
MICOM results for the localised and distributed groups

Construct	c observed	5% threshold	p (mean)	p (variance)	Full invariance
PAA	0.999718	0.999200	.6398	.9520	Yes
AUP	0.999645	0.996991	.8740	.6684	Yes
NAA	0.999509	0.999470	.6406	.5182	Yes
DA	0.999526	0.998446	.6662	.5638	Yes
AIE	0.999953	0.999251	.8430	.3308	Yes
AIA	0.998518	0.998814	.6274	.6104	No
DIT	0.999723	0.999132	.6824	.6082	Yes
DCVP	0.999547	0.999491	.9760	.7804	Yes
GDLE	0.999633	0.998741	.6180	.1634	Yes
RAUB	0.999701	0.998316	.7778	.5714	Yes

Note. MICOM = measurement invariance of composites; c = compositional correlation. Full invariance required configural and compositional invariance together with no evidence against equality of composite means and variances.

After the MICOM assessment, the groups showed broadly similar structural estimates: DCVP → GDLE was .695 in the distributed group and .706 in the localised group; DCVP → RAUB was .533 and .411; and GDLE → RAUB was .197 and .324. All 12 distributed-minus-localised permutation confidence intervals included zero. The largest contrast was NAA → DIT ($\Delta\beta = -.235$, 95% CI [− .257, .256], $p = .076$), making it a candidate for replication rather than evidence of a confirmed difference.

Power analysis qualifies this result. With the observed group sizes, the minimum detectable standardised difference was approximately .385 at 80% power and two-sided $\alpha = .05$, or .510 after the Bonferroni adjustment. The analysis therefore detected no large group differences, while smaller workflow-related differences remain unresolved. Online Resource 1, Table S16 summarises the focal group comparisons.

Taken together, GenAI was concentrated in generative stages, whereas the course-value mechanism showed broad continuity across narrower and broader integration patterns. Workflow breadth therefore provides meaningful contextual information without substituting for learning quality, disciplinary judgement, or responsible-use readiness.

5. Discussion

5.1 Overview and interpretation of the findings

The model revealed a hierarchy of educational mechanisms in which task appraisal initiated psychological responses, but course-value reaffirmation became the principal mechanism translating the GenAI-assisted experience into learning engagement and responsible-use behavioural intention. In the primary PLS-SEM, all prespecified paths were statistically supported, and the model explained 56.0% of course-value reaffirmation, 45.5% of generative-design learning engagement, and 43.7% of responsible-use behavioural intention. The multi-analytic methodological triangulation then distinguished the enduring educational core from more situational antecedents: design agency, identity-related professional revaluation, course-value reaffirmation, learning engagement, and behavioural readiness remained central, whereas exploration and anxiety were more sensitive to method specification.

The strong PAA → AIE effect (β = .648) identifies a clear opportunity-appraisal route. When GenAI helped students begin, visualise alternatives, and maintain momentum, it expanded the immediately available solution space and encouraged exploratory engagement. This pattern is consistent with design learning as a process of externalising, inspecting, combining, and revising possibilities rather than waiting for a fully formed solution (Cross, 2001; Schön, 1983). At the same time, the AIE → DCVP coefficient weakened after the common method factor was introduced. Exploration therefore appears to be an important task-level response, but not the most stable foundation on which students reaffirm the continuing value of formal design education.

The contrast between the two threat appraisals is more educationally consequential. Concern about simplified design training predicted AI-related anxiety more strongly than AI-output uncertainty perception did (.508 versus .238) and predicted design-identity threat more strongly as well (.533 versus .226). The stronger effects of concern about simplified design training indicate that students' psychological responses were shaped less by uncertainty surrounding a particular AI output than by uncertainty surrounding the educational process through which design competence is formed. Output uncertainty calls for verification, but simplified-training concern reaches further: it raises questions about whether sketching, experimentation, critique, iteration, and decision defence are being displaced before disciplinary judgement has developed. This distinction supports research that separates productive assistance from cognitive offloading and agency-eroding use (Wang et al., 2026; Yang et al., 2024).

Design agency and design-identity threat clarify how students responded to this concern. Design agency positively predicted course-value reaffirmation in the primary model (β = .283) and remained stable across the ten-factor and common-method CFA specifications (.305 to .336). Students who retained control over problem framing, evaluation criteria, adoption or rejection of generated suggestions, and final decisions were more likely to recognise why disciplinary education remained necessary. The positive DIT-to-DCVP effect reveals a compensatory process of professional revaluation. When GenAI challenges the exclusivity of output production as evidence of design competence, students may relocate the value of formal education from producing artefacts to framing problems, judging alternatives, defending decisions, and assuming responsibility. The direction of this effect persisted and strengthened in the method-factor model, although its magnitude was method-sensitive. By contrast,

anxiety changed direction after shared method variance was modelled, indicating that transient affective strain is not a reliable basis for course-value reaffirmation.

The findings empirically substantiate course-value reaffirmation as the core educational mechanism within the proposed model. DCVP → GDLE (β = .674) was the strongest core downstream path, DCVP also predicted RAUB (β = .462), and GDLE predicted RAUB (β = .254). The indirect effects show that course-value reaffirmation did more than predict two parallel outcomes. It transmitted the educational consequences of design agency and identity-related reappraisal to continued learning, while learning engagement further carried part of this association into responsible-use behavioural intention. The sequential DCVP → GDLE → RAUB indirect effect was β = .171, 95% CI [.092, .253], while PAA → AIE → DCVP → RAUB was β = .079, 95% CI [.042, .122], and DIT → DCVP → RAUB was β = .098, 95% CI [.045, .160].

The workflow and predictive analyses define the scope of this mechanism. Students primarily positioned GenAI as a generative and externalising resource, with use concentrated in visual generation and ideation rather than evenly distributed across judgement-intensive stages. The group comparison showed no systematic path differences across narrower and broader workflow involvement, while the power analysis indicates that smaller contrasts require larger samples. The model showed clear predictive relevance beyond the indicator-average benchmark, whereas the SmartPLS 4 linear benchmark retained a small overall advantage. These results place the downstream educational mechanism within a defined explanatory and predictive boundary.

5.2 Theoretical contributions

The first contribution is to extend task appraisal into educational value reappraisal. Existing GenAI research often asks whether students perceive a system as useful, risky, easy to use, or worth continuing to use. The present framework adds a different question: after an AI-assisted task, how do students reinterpret why formal disciplinary education remains necessary? Course-value reaffirmation captures this second-order appraisal. It explains how immediate opportunity and threat interpretations can be reorganised into a renewed recognition of disciplinary judgement, evaluative standards, professional formation, and accountable decision-making. In this sense, DCVP is not another acceptance attitude; it is the central explanatory mechanism through which a situated technological experience acquires educational meaning. This contribution speaks to recent debates on the educational implications of generative AI, academic transformation, and human-AI complementarity in higher education (Jeon & Lee, 2023; Watermeyer et al., 2024).

The second contribution is to reposition design professionalism under GenAI conditions. When visual and verbal outputs become faster and less scarce, the professional value of designers cannot rest primarily on producing polished artefacts. The stable agency effect and the positive identity-threat effect show that students increasingly locate professional value in problem definition, contextual interpretation, comparison of alternatives, authorship, decision justification, and responsibility for consequences. Identity threat is therefore not simply a negative outcome. It can initiate professional revaluation by

making visible the forms of competence that remain humanly and educationally consequential. This reframing aligns design education with traditions that define expertise through reflective judgement and situated action rather than output production alone (Cross, 2001; Schön, 1983; Suchman, 2007).

The third contribution is to distinguish workflow penetration, learning engagement, and responsible-use behavioural readiness. Task-stage coverage indicates where and how broadly GenAI enters a design process; GDLE indicates whether students continue to investigate and improve the work; RAUB indicates readiness to verify, revise, disclose, and retain process evidence. These dimensions are related but not interchangeable. A tool may appear in many stages without deepening learning, and limited stage coverage may still prompt strong judgement and accountability. The direct and indirect DCVP effects further show that responsible use is grounded both in sustained engagement and in a distinct recognition of professional obligation. This distinction moves responsible GenAI integration beyond rule compliance and gives it a substantive educational foundation. It also aligns with emerging work linking AI use to differentiated forms of engagement, competence development, and responsible academic practice (Pedraja-Rejas et al., 2026; Zhu & Yang, 2026).

5.3 Practical implications for GenAI-integrated design education

The findings support curriculum responses that make disciplinary value, learner agency, formative practice, and accountability visible wherever GenAI enters design work. Table 13 provides a concise finding-to-action map; the following paragraphs explain how these responses can be enacted.

Table 13
Empirical findings and implications for GenAI-integrated design education

Key empirical finding	Educational interpretation	Recommended curriculum response
DCVP strongly predicted GDLE and RAUB	Students act on GenAI more educationally when they recognise the continuing value of disciplinary judgement and standards.	Make problem framing, evaluation criteria, critique, decision justification, and accountability explicit in briefs and rubrics.
Design agency remained a stable predictor of DCVP	Retained control over framing and evaluation anchors the value of formal design learning.	Use a think-first-then-AI sequence: define users, constraints, evidence, and criteria before prompting; document acceptance and rejection decisions.
DIT positively predicted DCVP, with direction reinforced in the method-factor model	Identity tension can trigger professional revaluation from output production toward authorship, judgement, and responsibility.	Require process portfolios, attribution statements, change rationales, and oral defence of key design decisions.
NAA predicted anxiety and identity threat more strongly than AUP	Students are especially concerned about bypassing the formative process through which competence is developed.	Protect sketching, experimentation, precedent analysis, critique, iteration, and decision defence as assessed learning activities.
GenAI use concentrated in visual generation and ideation	Workflow penetration is uneven and does not itself indicate learning quality or responsible use.	Apply stage-specific governance: source checks for research, comparison and fixation checks for ideation, revision rationales for development, and disclosure for presentation support.
DCVP affected RAUB directly and indirectly through GDLE	Responsible-use readiness reflects both sustained learning effort and a distinct accountability pathway.	Assess verification, substantive revision, disclosure, and process documentation as evidence of professional learning.

Note. Recommendations translate the empirical pattern into curriculum actions; they do not represent independently tested interventions.

First, course-value reaffirmation should be designed into the curriculum rather than left as an implicit message. Briefs, critiques, and assessment rubrics can state explicitly which forms of judgement remain educationally central: defining the problem, establishing criteria, interpreting context, comparing alternatives, explaining revisions, and accepting responsibility for the final decision. Students should be asked to articulate how these criteria changed across the project and why the selected outcome is preferable to generated alternatives. Such practices make the value of disciplinary learning observable in the work itself.

Second, the stable role of design agency supports a think-first-then-AI sequence for selected tasks. Before prompting a system, students can define the intended user, problem boundaries, constraints, evidence requirements, and provisional evaluation criteria. They can then use GenAI to expand alternatives, but must record which suggestions were accepted, transformed, or rejected and on what

grounds. This sequence preserves the exploratory benefits of GenAI while ensuring that problem framing and evaluative authority remain with the learner. Process records function here as evidence of authorship and reasoning rather than as surveillance.

Third, the stronger NAA effects indicate that programmes should protect the formative practices through which judgement develops. Sketching, material or visual experimentation, precedent analysis, peer critique, iterative revision, and oral decision defence should remain assessable components even when generated outputs are permitted. Assessment should reward the quality of comparison, transformation, and justification rather than the fluency or polish of the first result. Instructors can also introduce tasks in which students diagnose weak or misleading AI outputs, reconstruct the missing reasoning, and demonstrate how disciplinary methods improve the result.

Finally, governance should be stage-specific rather than uniform. Reference search requires source verification and provenance records; ideation and visual generation require alternative comparison and fixation checks; evaluation and revision require explicit criteria and change rationales; copy and presentation support require disclosure without treating polished expression as proof of understanding. Across stages, verification, substantive revision, disclosure, and process documentation should be integrated into assessment as forms of professional practice (Chan, 2023; UNESCO, 2023).

Such an approach connects responsible-use behavioural intention to the same learning processes that produce design judgement and gives students a positive account of why accountability matters (Amershi et al., 2019; Long & Magerko, 2020; Shin, 2021; Shneiderman, 2020).

6. Conclusion, Limitations, and Future Research

6.1 Conclusion

This study developed and tested a task-anchored model explaining how GenAI-assisted design experiences are translated into continued learning and responsible-use behavioural intention. The results revealed a hierarchy of educational mechanisms: task appraisals initiated exploratory, affective, and identity-related responses, but course-value reaffirmation became the principal transmission mechanism. Positive AI appraisal strongly supported exploration, whereas concern about simplified design training had stronger effects on anxiety and design-identity threat than AI-output uncertainty perception. Students therefore appeared to respond less to uncertainty surrounding a particular generated output than to the possible erosion of the educational processes through which design competence is formed.

Course-value reaffirmation directly strengthened responsible-use behavioural intention and also operated indirectly through generative-design learning engagement. Multi-analytic methodological triangulation refined rather than weakened this account: the downstream mechanism linking course-value reaffirmation, learning engagement, and behavioural readiness remained stable, together with the contribution of design agency, whereas several upstream exploratory and affective routes were method-

sensitive. Workflow evidence further indicated that students primarily positioned GenAI as a generative and externalising resource concentrated in visual generation and ideation. The breadth of workflow use should therefore not be treated as equivalent to learning quality, professional judgement, or responsible-use readiness.

The central theoretical implication is that GenAI does not eliminate the value of design education; it changes how that value is recognised. As generation becomes faster and less scarce, the educational centre of gravity shifts from output production to problem framing, evaluative judgement, professional identity, decision justification, and responsibility. The central educational challenge is consequently not how extensively GenAI enters the design workflow, but whether its use strengthens the judgement, agency, and accountability through which design competence is formed.

6.2 Limitations and Future Research

The cross-sectional, self-report design establishes a well-specified pattern of associations, while the method-factor sensitivity analysis shows that some upstream estimates depend on measurement specification. The stable downstream paths provide a basis for multi-wave studio research that measures appraisals after specific tasks, course-value reaffirmation during critique and revision, and later engagement and accountability outcomes. Combining surveys with prompt histories, version records, critique observations, and instructor ratings would provide a stronger account of temporal development and reduce dependence on a single source.

The task-stage module was complete for 210 respondents because 93 participants did not enter or complete the relevant questionnaire branch. The available records captured breadth and location, but not duration, intensity, sequence, prompt depth, tool type, or the degree to which generated material was transformed. The observed group sizes provided sensitivity to moderate-to-large path differences, while smaller boundary effects require larger and more balanced samples. Future studies should collect mandatory stage-level logs across multiple courses and tasks, link each stage to artefacts and revisions, and model workflow breadth together with intensity, sequence, task stakes, and disciplinary specialisation.

RAUB measures responsible-use behavioural intention and behavioural readiness rather than independently logged conduct. Future work should connect the present mechanism to observed verification, substantive revision, disclosure, citation or provenance records, and retention of process evidence. External-cohort prediction and longitudinal follow-up would also clarify whether course-value reaffirmation prospectively predicts enacted responsibility beyond simpler antecedent models. These extensions would connect task appraisal, professional revaluation, and learning engagement to the accountable practices through which responsible GenAI use becomes visible.

Declarations

Data Availability Statement

The de-identified model-data export and supporting analysis materials underlying the reported results are available from the corresponding author upon reasonable request, subject to institutional data-governance requirements and the consent restrictions governing the anonymous survey. The raw response workbook is not publicly available because it contains response-level and source-row information.

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Figures

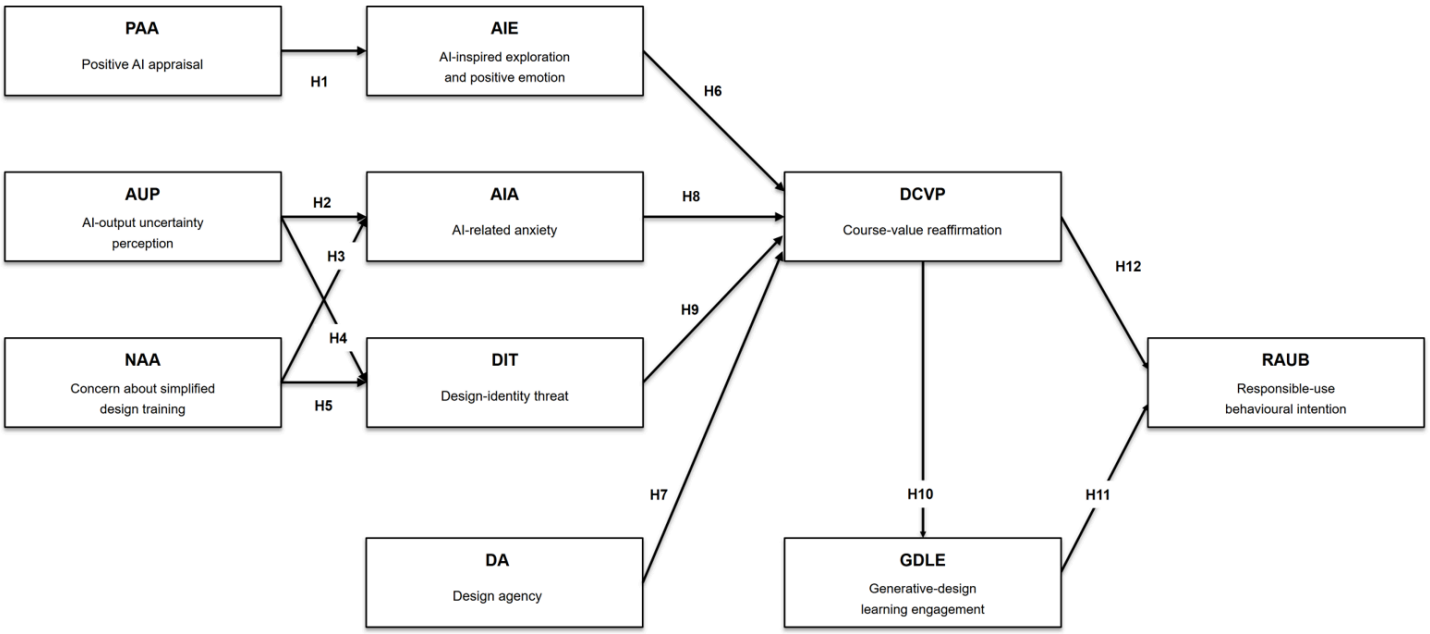


Figure 1

Proposed research model and hypotheses

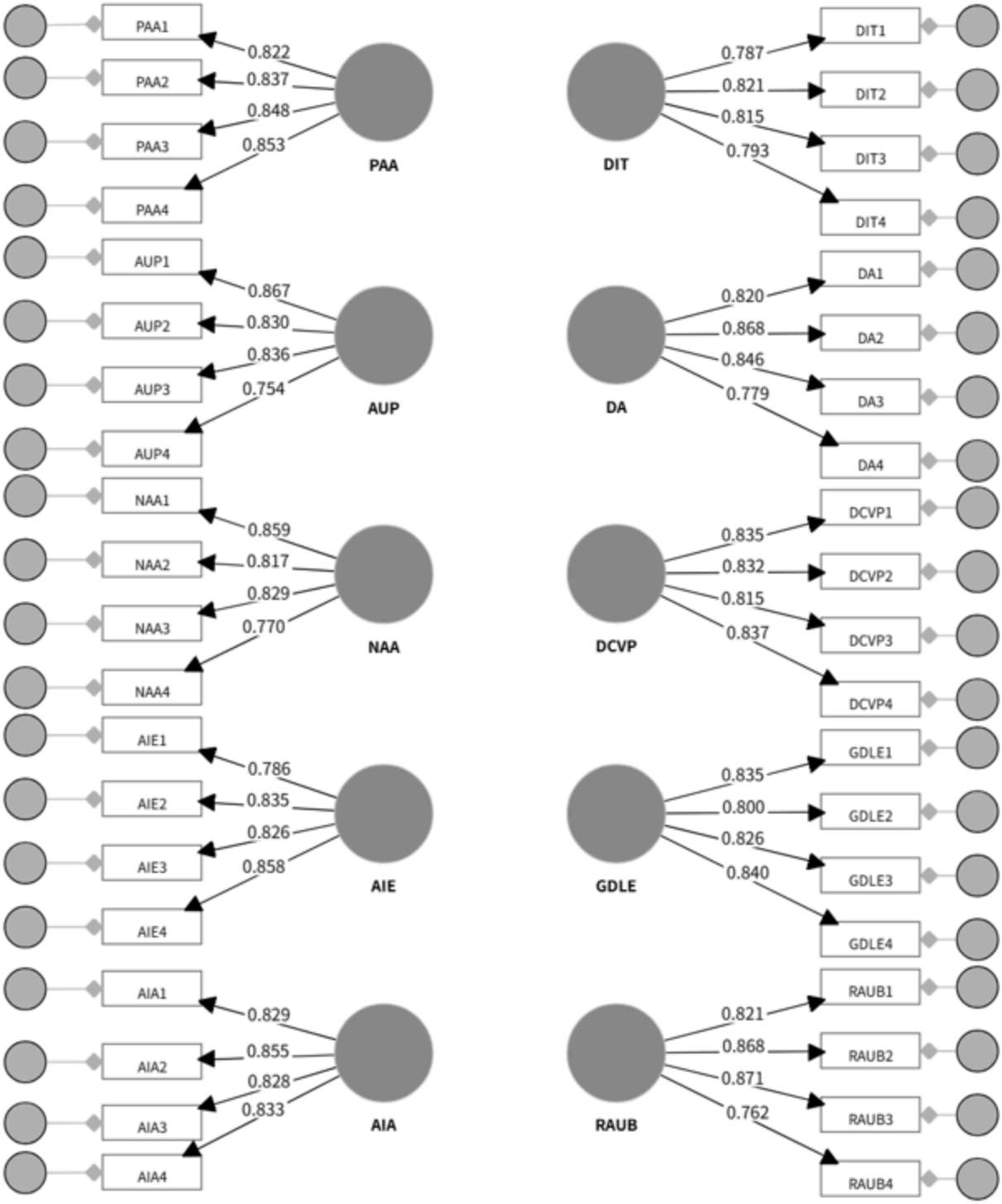


Figure 2

Confirmatory factor analysis model of the ten-factor measurement structure. Values represent standardised factor loadings. All loadings were significant at $p < .001$. Factor correlations and indicator error terms are omitted for visual clarity

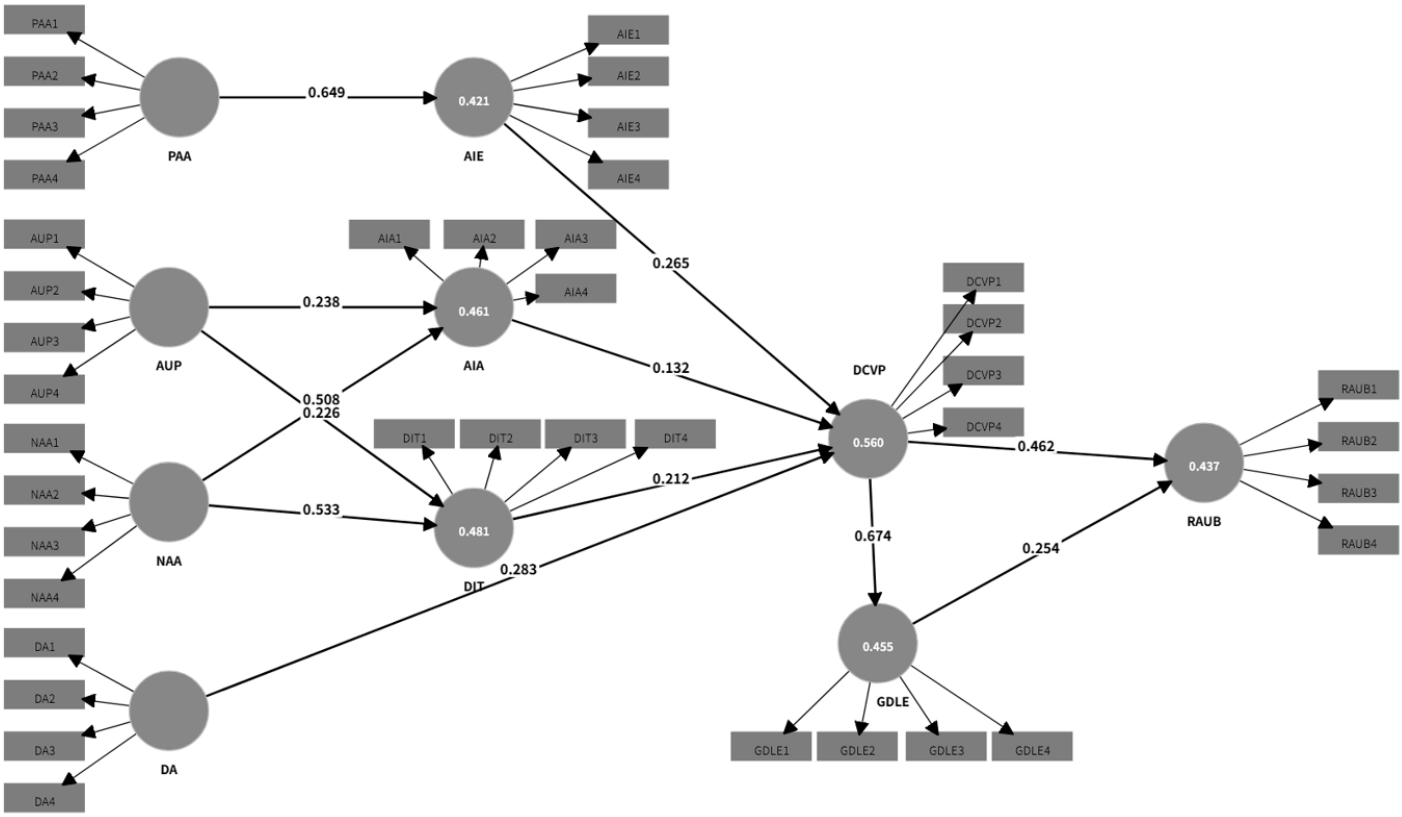


Figure 3

PLS-SEM structural model estimates and hypothesis support. Values on structural paths are standardised path coefficients (β); values within endogenous constructs are R^2. All twelve hypothesised paths were significant based on 5,000 bootstrap samples

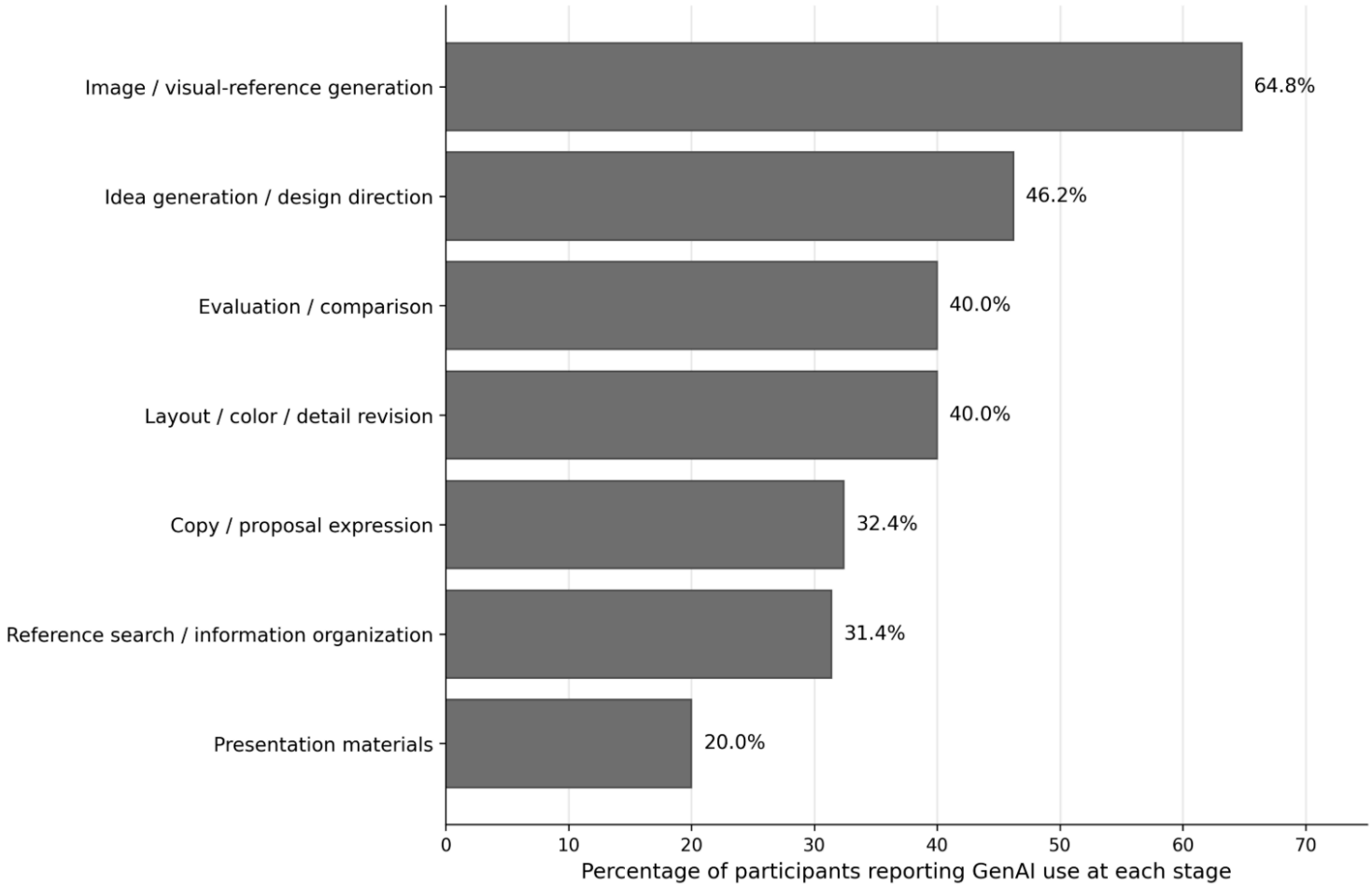


Figure 4

GenAI participation across design-task stages