

Application of Generative Models for Personalized Design Education: Adaptive Approaches in Art-pedagogical Learning

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Abstract—This article introduces Generative Design Adaptive Learning Environment (G-DALE), an adaptive generative learning framework designed to personalize creative development in art and design education. The framework combines learner profiling, adaptive sequencing of generative tasks, multimodal feedback, and real-time instructional support to align learning activities with individual creative needs. We conducted a four-week study with 72 participants to evaluate students' engagement with generative Artificial Intelligence (AI) tools and the influence of adaptive mechanisms on their performance. The results demonstrate notable gains in creative quality, including deeper conceptual thinking, improved visual coherence, and greater stylistic stability (paired-samples t-tests, all $p < 0.001$, Cohen's $d = 0.65\text{--}0.77$). Students also showed higher productivity through faster iteration cycles and increased design variation. Cluster analysis revealed distinct learner adaptation profiles, indicating that personalization emerges through differentiated patterns of cognitive scaffolding, refinement guidance, and style alignment. Overall, the findings show that, when supported by a structured pedagogical model, generative AI can serve as an effective educational agent that fosters learner independence in creative decision-making and provides a structured pedagogical pathway for personalized design instruction.

Keywords—artificial intelligence in education, learning technology, instructional technology, creativity, adaptive learning systems

I. INTRODUCTION

Generative Artificial Intelligence (GAI) is widely recognized as one of the most important technologies in contemporary education, offering educators and students expanded opportunities for personalized, creative, and adaptive learning [1]. Personalized learning, which researchers have historically viewed as an important element in the achievement of improved educational outcomes, is often limited in its ability to address the various and diverse needs of each student, particularly in relation to the art/design field, which comprises many types of visual literacy, creative style, conceptual thinking, and development rate differences. In addition, there is often insufficient continuous access to individualized teacher feedback, an important element in the artistic growth of both students and teachers. Overall, the current education system lacks sufficient personalization of its curriculum and educational practices for design schools [2].

The development of new multimodal generative models will create new possibilities for changing this situation [3].

Text-image diffusion models (e.g., GAN (generative adversarial network)-based image-to-image translation), transformer-based language models, and hybrid visual-semantic models can help identify a student's design style, recommend design concepts, create visual representations of design ideas, and support the iterative refinement of design. Research on GAI in fields such as engineering, science, and language acquisition demonstrates how GAI can facilitate task personalization, enhance learner engagement, and provide tailored feedback to individual learners. However, the use of GAI in art/design education remains limited compared with more traditional forms of education [4]. Many existing studies have treated GAI as a creative tool rather than an adaptive pedagogical tool to help students achieve their artistic goals. In the G-DALE framework, generative AI acts as an educational agent performing adaptive diagnosis, pedagogical sequencing, and formative feedback—functions that extend beyond content generation.

There are several key deficiencies still present in relation to current AI tools. While current AI tools can generate visual products, they do not necessarily take into consideration the student's conceptual knowledge of a design product or their level of creative thinking. They offer limited support for developing one's artistic judgment, critical reflection, and creative autonomy, which represent core competencies in design education. There is also a risk associated with dependence on AI, a potential loss of creative identity, ethical issues, and cognitive load from using complex tools [5]. These challenges illustrate that the use of generative models in design education requires a structured pedagogical framework for their implementation.

This research investigates how generative AI can enhance personalized learning in design. The focus of this research is on developing an educational process in design training at the university level. The investigation will focus on the use of generative AI models to support personalized learning and the adaptation of design tasks. The research aims to develop and validate a framework for the adaptive use of generative AI to provide individualized tasks, support creative thinking, and improve the process of reflection and feedback. In doing so, G-DALE advances educational technology across four dimensions: adaptive learning systems, learning analytics, AI-supported feedback, and multi-level educational evaluation [6]. The innovative contributions of this research are to:

- Provide a perspective on generative AI as an educational agent rather than just a creative tool.
- Develop a structured model for using generative AI that includes student profiling, multimodal content generation, adaptive task sequencing, and AI-guided reflective responses.
- Design an experiment to measure the impact of personalized use of generative AI on creative and conceptual products.
- Explore the pedagogical and ethical conditions that support the responsible use of AI in art and design education.

The research builds on the premise that a pedagogy-supported framework using AI may result in improved personalization in design education, enhanced students' creative and analytical skills, and greater effectiveness of the learning process.

Accordingly, four Research Questions (RQs) guide this study. **RQ1:** To what extent does G-DALE improve creative performance (conceptual depth, visual coherence, and stylistic consistency) relative to pre-intervention baseline scores? **RQ2:** How does G-DALE influence workflow efficiency in terms of design iteration time and number of design variations? **RQ3:** What distinct patterns of adaptive personalization emerge among learners interacting with G-DALE? **RQ4:** How do learners perceive the benefits and limitations of AI-supported adaptive design instruction?

The structure of this article is as follows: the introduction includes the relevance, objectives, innovations, and the study's hypothesis. The literature review provides an overview of existing literature regarding generative AI, personalized learning, and AI-based design education. The methodology section outlines the framework and describes the research and the experimental design used in this study. The results section presents the outcomes of this study and discusses their implications. Finally, the conclusion summarizes the main findings and identifies opportunities for further research.

II. LITERATURE REVIEW

Generative Artificial Intelligence (GAI) has emerged as a promising technology for supporting personalized learning and creative development in education. Recent studies indicate that generative models enhance ideation, accelerate iterative workflows, and enable adaptive feedback mechanisms in creative learning environments [7–9]. However, existing research remains fragmented, particularly in structured design education, where pedagogical integration and personalization strategies are still developing.

Several studies emphasize the role of transformer-based and diffusion models in improving visual ideation and conceptual exploration. For example, researchers have reported 20–30% improvements in task relevance and conceptual accuracy in transformer-based new media art pedagogy contexts; however, these improvements refer to task-relevance metrics rather than rubric-assessed creative quality and represent a different evaluation framework from the present study [7]. Similarly, text-to-image prompting approaches show potential for supporting artistic experimentation and visual concept development [10]. Despite these advantages, challenges remain in integrating

generative models into formal design curricula, particularly due to variability in output quality, limited domain-specific datasets, and insufficient pedagogical alignment [11]. These findings suggest that generative tools require structured instructional frameworks to ensure consistency and alignment with learning objectives.

Another group of studies focuses on collaborative and interactive uses of generative AI. Research using tools such as ChatGPT and text-to-image systems demonstrates improvements in creative problem-solving and team creativity performance [8]. These systems support idea generation and facilitate efficient completion of creative tasks. However, personalization mechanisms are often limited because learners with varying levels of expertise receive similar forms of support. Researchers have proposed adaptive learner modeling approaches, such as clustering and knowledge tracing, to address this limitation [12], although their application to design education remains limited.

Research on participatory and project-based creative learning further highlights the potential of generative tools to increase engagement and experimentation. Collaborative design environments supported by AI enhance student participation and encourage exploration [13]. Nevertheless, computational constraints and lack of domain-specific personalization often restrict practical implementation. Technical solutions such as lightweight diffusion models and adaptive systems have been proposed to improve performance and stability [14]. Yet these approaches still lack adaptive pedagogical mechanisms tailored to individual learners.

Studies investigating generative AI within creative workflows also emphasize the ability of GAN-based and diffusion systems to produce multiple stylistic variations from limited datasets [15]. While this capability supports exploration, issues such as mode collapse, output inconsistency, and limited pedagogical alignment remain. Structured prompting and guided refinement cycles offer potential solutions [10], though their integration with competency-based design learning objectives remains insufficiently explored.

Research in adaptive and immersive learning environments further demonstrates the importance of generative learning strategies within dynamic instructional cycles. Findings indicate that adaptive sequencing and generative feedback improve learning outcomes compared to static instructional approaches [16]. However, existing implementations often rely on fixed learning sequences and do not incorporate personalization of visual thinking or stylistic development [17]. These limitations highlight the need for adaptive pipelines that integrate generative AI with learner-centered instructional design.

Learner perception studies also support the use of generative AI for iterative creative development. Survey results show that students value AI-generated suggestions to accelerate ideation and refinement [9]. At the same time, concerns regarding trust, consistency, and misinterpretation of creative intent persist. Researchers have proposed hybrid approaches that combine instructor guidance with AI-generated feedback to address these issues [18], though comprehensive adaptive feedback systems for design education remain lacking.

Finally, recent literature emphasizes ethical considerations associated with generative AI in education. Studies identify risks related to authorship, transparency, dataset bias, and preservation of creative identity [19–21]. These concerns highlight the importance of developing pedagogically grounded and ethically responsible frameworks for integrating generative AI into design education.

Overall, the reviewed studies demonstrate that generative AI has strong potential to enhance creativity, engagement, and personalization. However, gaps remain in structured pedagogical integration, adaptive learner modeling, and ethical implementation. These limitations motivate the development of the Generative Design Adaptive Learning Environment (G-DALE) framework, which combines learner profiling, adaptive sequencing, multimodal generation, and structured feedback within a unified pedagogical model.

III. MATERIALS AND METHODS

This research creates and verifies an adaptable educational approach that integrates Artificial Intelligence (AI) creation within the framework for individualizing design education. This approach (called G-DALE) is employed systematically in seven steps: analyzing a learner's profile, planning generative activities, preparing materials, creating with AI assistance, customizing to a learner's level, and assessing at

multiple levels. Methodologically, the research has two parts: first, we derive the G-DALE framework from theories of art pedagogy and generative AI; second, we apply the G-DALE model in a four-week design course to investigate how learners interact with generative tools to enable personalization in creative development.

A. The G-DALE Adaptive Learning Framework

As shown in Fig. 1, the G-DALE framework consists of seven phases that guide learners through the steps leading up to an evaluation of their work. Phase 1 includes profiling learners by the types of creative learners they are and their readiness to use technology in their learning. Phase 2 is to create learning goals and set up the generative tasks to achieve them. Phase 3 prepares all instructional materials and aligns the live and/or online activities. Phase 4 has learners actually produce their design products/environments/libraries with assistance from AI. Phase 5 provides for the teaching actions, including guidance, critique, and collaborative exploration. Phase 6 allows adjustments to learners' activities based on learners' needs. Finally, Phase 7 integrates diagnostic, formative, and summative assessments to support creative progress towards achieving the envisioned designs (Fig. 1).

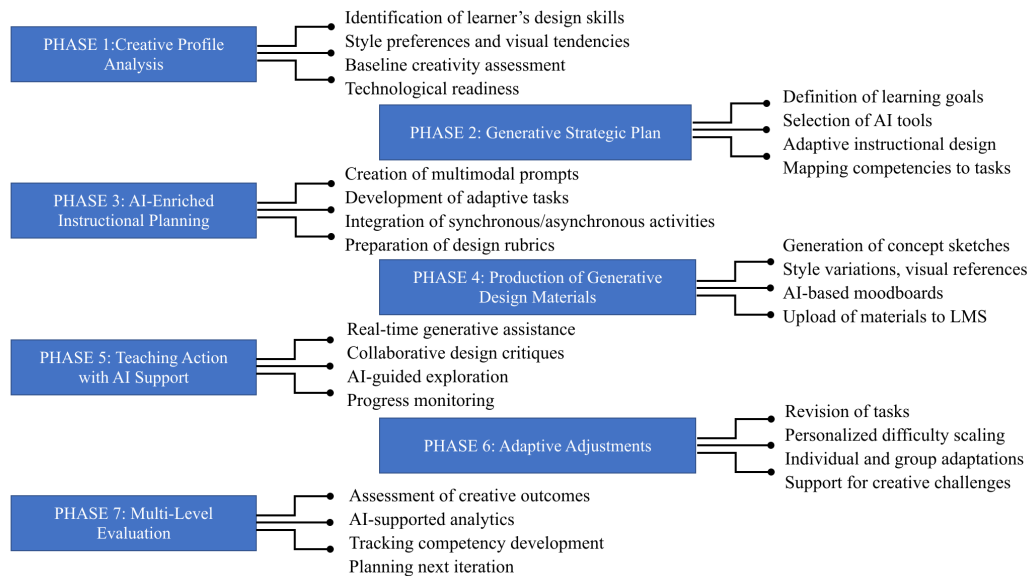


Fig. 1. The structure of the G-DALE framework for personalized design education.

B. Participants and Learning Context

The G-DALE model was tested in a four-week course called Generative Design Studio for Art Education, with each week incorporating AI/generative tools and personalized design learning delivered through blended methods. The study featured a sample of 72 students, comprising senior art and design students, pre-service art teachers, and early-career teachers. All learners followed the same instructional structure as outlined in the G-DALE framework's seven stages.

The demographic profile in Table 1 shows that the participant sample was very diverse regarding age, educational background, and familiarity with AI tools. This diversity allowed for more comprehensive analyses of how

generative technologies support personalized creative development (Table 1). The following subsections discuss how we implemented the G-DALE framework during the experimental course and how learners interacted with each of its seven stages. A one-way MANOVA (multivariate analysis of variance) confirmed that educational background had no significant effect on post-intervention rubric performance (Pillai's $V = 0.114$, Approx. $F(9, 204) = 0.893$, $p = 0.532$), supporting the generalizability of findings across participant subgroups.

The study employed a single-group pretest–posttest design. Data collection included baseline rubric scores at the start of Week 1 before any G-DALE-mediated instruction and post-intervention scores at the end of Week 4. All submitted design artifacts were anonymized and assigned random codes

before scoring. Two experienced design instructors independently scored each artifact using a standardized three-criterion rubric (Conceptual Depth, Visual Coherence, Stylistic Consistency; each on a 1–10 scale), blind to the artifact’s temporal origin. Inter-rater reliability was confirmed using the Intraclass Correlation Coefficient (ICC); ICC (3,1) values ranged from 0.78 to 0.86 across all criterion–occasion combinations, with all lower-bound 95% Confidence Intervals (CIs) at or above 0.67, meeting the “excellent” agreement threshold throughout. We acknowledge the absence of a control group as a limitation; observed gains may partly reflect practice or novelty effects, and future research should employ comparative designs. This study did not require formal ethics committee approval under applicable institutional guidelines; all participants were adults who provided voluntary informed consent, and participation had no bearing on course grades or academic standing.

Table 1. Demographic characteristics of study participants ($n = 72$)

Variable	Category	Frequency (n)	Percentage (%)
Age	18–22	28	38.9%
	23–27	24	33.3%
	28–35	13	18.1%
	36+	7	9.7%
Gender	Female	45	62.5%
	Male	27	37.5%
Educational background	Design, Graphic Design, Visual Design	32	44.4%
	Art Education, Fine Arts Pedagogy	21	29.2%
	Media Technologies, Digital Media, Multimedia Design	11	15.3%
	Computer Science, Information Systems, Software Engineering	8	11.1%
Experience with AI tools	Low	29	40.3%
	Medium	31	43.1%
	High	12	16.6%
Teaching or learning experience	<1 year	25	34.7%
	1–3 years	22	30.6%
	4–7 years	15	20.8%
	>7 years	10	13.9%

To support reproducibility, we anchored each criterion to three performance bands rather than scoring it as a single, undifferentiated number. Low scores (1–3) reflected work with little evidence of intentional development — for Conceptual Depth, an absence of a discernible design rationale; for Visual Coherence, disconnected or unresolved visual elements; for Stylistic Consistency, no sustained stylistic direction across the piece. Mid-range scores (4–7) reflected partial development — an emerging but not fully articulated concept, generally coherent composition with noticeable inconsistencies, or a stylistic approach applied unevenly across the work. High scores (8–10) reflected fully realized performance — conceptually rich and well-reasoned design intent, a unified and intentional visual composition, and a consistently maintained personal style throughout the artifact. We trained both instructors on these anchor descriptions before scoring to standardize judgment across raters.

To address transparency and authorship concerns, all participants received explicit instruction to critically evaluate AI-generated outputs before integrating them into their work, framing generative AI as a resource subject to human

judgment rather than an authoritative design authority. Students were required to submit an AI prompt log alongside each artifact, documenting which elements were AI-generated and which were independently developed, thereby maintaining clear attribution of authorship. We maintained data privacy by using anonymized institutional accounts for all AI tool interactions; no personally identifiable learner data was transmitted to or retained by external model-training pipelines. To mitigate stylistic homogenization, we configured the Adapt_Style mechanism to present divergent stylistic prompts when learner iterations exhibited low variance, actively counteracting convergence toward generic aesthetic outputs.

C. Operational Flow of the G-DALE Seven-phase Model

Fig. 2 shows Phases 2 and 3 of the G-DALE process. The second phase of the G-DALE framework outlines the development of a comprehensive generative learning plan, including learning goal alignment, design competency alignment, weekly unit definition, and AI tool selection, based on the learner profile, for the entire course (Fig. 2). This plan indicates when students will use models, prompt and receive support using adaptive AI tools, thereby providing a gradual and consistent way to introduce generative tools throughout the entire four-week module.

The third phase of this framework is to design the specific activities that students will complete as part of the learning process during the course. The activities include guided exploration of AI tools; iterative design tasks; peer exchanges; and feedback cycles supported by generative models. Each activity is adapted to different skill levels so that students each develop their own personal workflow. In Phase 3, instructional planning ensures that all activities support individual creative development and equip learners with the knowledge needed for project work in later phases.

In Fig. 3, we can see a visual representation of how G-DALE organizes and supports both synchronous and asynchronous learning, as well as the generative resources that support the different phases of learning. The visual also provides a timeline perspective for each phase of the four-week course. Phase 4 focuses on developing AI-assisted design tools. In this phase, students will use instructor-provided prompts to develop visual outputs, explore different versions of their designs, and finally create several versions that reflect different styles. In Phase 5, instructors bring this same activity into active teaching situations. Instructors support students through critique, demonstrations, and iterative improvements, while AI tools provide ongoing suggestions and real-time feedback. In Phase 6, we make adaptive adjustments based on each student’s progress and, where necessary, adjust the difficulty of each task to provide the necessary level of assistance. Finally, we evaluate all phases through a combination of multi-level evaluations—analytic scores, teacher assessment, and student reflection—that together keep G-DALE both structured and flexible, allowing personalization to emerge throughout the design process.

Fig. 4 shows the activities and workflow in Phase 3 of the G-DALE framework’s elements used to move from planned generative tasks to active creative work in the LMS (learning management system). During this phase, all students receive

AI-supported instructional materials, multimodal prompts, and project briefs specifically aligned with their learning profiles. The LMS is the primary workspace for the student as they explore generative tools, work through iterative tasks,

and receive feedback from both AI systems and the instructor. With this structure, students can all progress at their own pace while receiving appropriate and timely guidance.

PHASE 2 – STRATEGIC PLAN								
Unit	Weeks	Intended Results	Competencies	Contents	Synchronous Activities	Asynchronous Activities	Resources	Evaluation
Unit 1: Foundations of Generative Design	Week 1	Understand generative models; identify personal style tendencies	C1: Model literacy C2: Prompt logic	Overview of LLMs, diffusion models, ControlNet	Live showcase of model generations	Intro readings + tutorials	Sample prompts, SDXL gallery	Diagnostic test, rubric
Unit 2: Prompt Engineering & Style Exploration	Week 2	Apply structured prompting; produce varied design iterations	C3: Style manipulation	Style prompts, constraints, variation prompts	Guided prompting workshop	Prompt-variation exercise	Style reference sheets	Formative feedback
Unit 3: Personalized AI Workflow	Week 3	Build workflows adapted to skill level	C4: Personalized workflow design	Adaptive assistance, critique loops	Instructor-led critiques	Iterative refinement	AI feedback tutor	Mid-module check
Unit 4: Synthesis & Final Design	Week 4	Produce personalized creative solution	C5: Creative synthesis	Integration of techniques	Final critique	Independent project	Project toolkit	Summative evaluation
PHASE 3 – INSTRUCTIONAL PLANNING: STUDENT ACTIVITIES								
Activity Type		Description		Tools		Expected Outcomes		
Generative exploration		Students generate multiple visual variants responding to prompts		SDXL, ControlNet		Visual ideation		
Adaptive tasks		System assigns difficulty-adjusted tasks		LLM-based planner		Personalized learning flow		
Collaborative exchanges		Students compare outputs and discuss variations		LMS forums, shared boards		Peer learning		
Iterative critique		Joint teacher + AI feedback cycles		AI critique engine		Improvement of creative reasoning		

Fig. 2. Strategic plan and Instructional design matrix for framework.

PHASE 5 – TEACHING ACTION WITH AI SUPPORT				
Activity Type	Description	Tools	Instructor Role	Expected Outcomes
Real-time generative assistance	Students request variations, refinements, and alternates during design work	SDXL, Midjourney, ControlNet	Guide prompt refinement; ensure ethical & stylistic correctness	Increased speed of idea exploration
AI-supported critiques	AI generates structured feedback (composition, balance, color logic)	AI Critique Engine	Validate AI feedback; add higher-level interpretation	Improved analytical reasoning
Collaborative design reviews	Students compare AI-generated & human-generated iterations	LMS forums, shared boards	Facilitate discussion & peer exchange	Enhanced reflective practice
Guided exploration sessions	Teacher demonstrates workflows combining human & AI steps	Screen-share tools	Model iterative thinking	Improved design process awareness
Progress monitoring	AI tracks learner trajectories & flags stagnation	Learning analytics dashboard	Intervene when plateau detected	Personalized pacing and support
PHASE 7 – MULTI-LEVEL EVALUATION				
Evaluation Type	Description	Criteria / Rubric	Tools	Expected Outcomes
Diagnostic assessment	Initial check of model literacy, prompt skills, creative baseline	Understanding of LLM concepts; style-awareness; task comprehension	Diagnostic quiz, sample prompt tasks	Learner profile for adaptive pathways
Formative evaluation	Continuous evaluation during activities	Iteration quality, variation depth, prompt control	AI analytics, teacher scoring	Mid-course corrections
Summative evaluation	Final assessment based on project output	Originality, coherence, technique integration, generative reasoning	Portfolio submission + rubric	Demonstration of skill development
AI-assisted analytics	Automated tracking of creativity metrics	Diversity of outputs, refinement behavior, time-on-task	Analytics dashboard	Objective progression metrics

Fig. 3. Instructional design matrix for implementing the G-DALE framework.

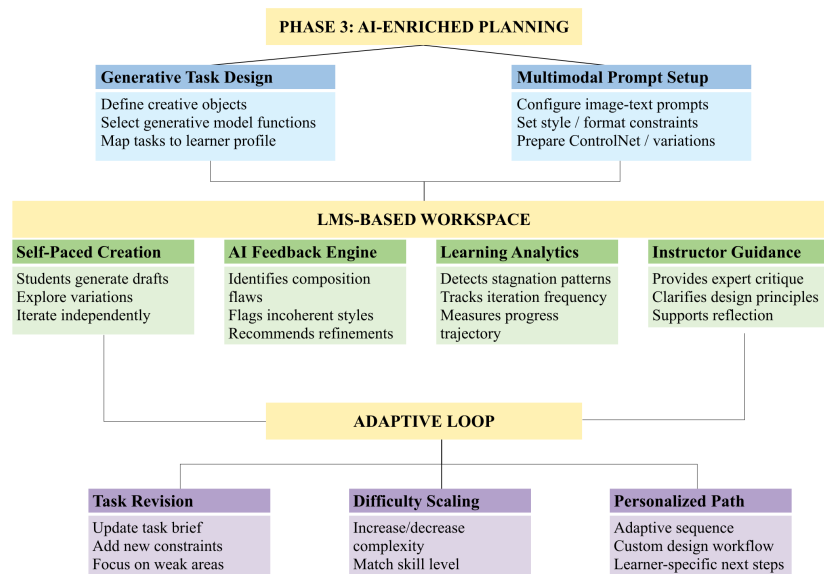


Fig. 4. AI-enriched workflow of instructional planning and adaptive support.

As students begin drafting their design, the LMS continually analyzes their interactions and identifies which components require further attention. The LMS has built-in adaptive mechanisms (i.e., task revision, targeted refinement suggestions, and task difficulty scaling) that will dynamically evolve the learning process based on each student's interactions. By making these adjustments, the LMS can provide an optimal level of challenge while supporting students' creative development. The combination of AI analytics and instructor guidance allows for a more personalized experience that helps each student create their own creative path, leading to deeper project development in future phases. Specifically, we tracked three behavioral indicators: Adapt_Difficulty (frequency of task complexity adjustments), Adapt_Refinement (proportion of AI refinement suggestions accepted), and Adapt_Style (alignment between AI-proposed and learner-selected stylistic outputs). These indicators dynamically triggered task revision, difficulty scaling, or style-alignment support.

IV. RESULTS AND DISCUSSION

A. Creative Performance Improvement

Fig. 5 compares creativity scores across the rubric criteria of conceptual depth, visual coherence, and stylistic consistency before and after the application of the G-DALE framework to all three rubric-based dimensions. It shows a significant shift in performance across all three dimensions after using the G-DALE framework. Participant performance increased by 29%–33% after using the G-DALE framework, indicating statistically significant and practically meaningful improvements across all dimensions.

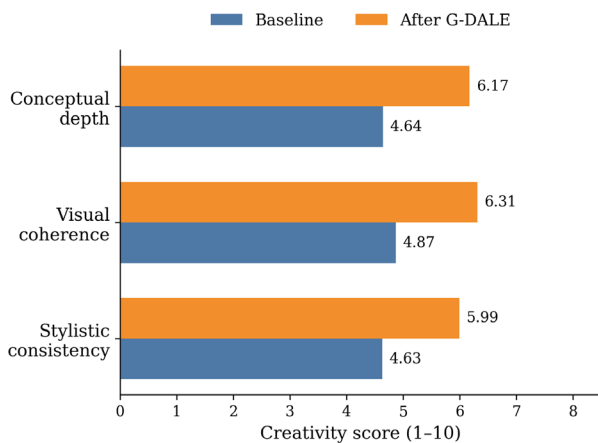


Fig. 5. Creative performance before and after the framework.

Table 2. Rubric criterion descriptive statistics and paired-samples t-test results ($N = 72$)

Rubric Criterion	Pre M (SD)	Post M (SD)	t(71)	p	d [95% CI]
Conceptual Depth	4.64 (1.78)	6.17 (1.99)	-6.55 < 0.001		0.771 [0.506, 1.033]
Visual Coherence	4.87 (1.64)	6.31 (2.07)	-6.22 < 0.001		0.733 [0.470, 0.991]
Stylistic Consistency	4.63 (1.63)	5.99 (2.07)	-5.52 < 0.001		0.651 [0.394, 0.903]

Paired-samples t-tests confirmed statistically significant improvements across all three rubric criteria (all $p < 0.001$). Effect sizes were large for each dimension ($d = 0.651$ – 0.771), indicating practically meaningful gains. The consistency of

large effect sizes across all three criteria suggests that G-DALE produced broad-based creative development rather than improvement concentrated in a single dimension. Notably, the 95% confidence intervals for all three dimensions were entirely above zero, further corroborating the reliability of the observed gains. Table 2 presents the full descriptive statistics and inferential results.

Conceptual depth showed the most substantial improvement, suggesting that reduced technical production demands under G-DALE enabled learners to reallocate cognitive resources toward conceptual intent and design reasoning. Students engaged more directly with the communicative and expressive dimensions of their design decisions, reflecting a shift from generic to more idiosyncratic visual choices. Students also demonstrated improvement in stylistic consistency—an outcome particularly notable given the heterogeneity of the participant sample—indicating that generative scaffolding not only elevated mean performance but also stabilized thematic coherence across learners. The uniform improvements across all three rubric criteria confirm that G-DALE benefits the entire creative process, from conceptualization through visual refinement, rather than privileging any single stage.

B. Efficiency and Productivity through Design Task Metrics

Fig. 6 presents the workflow metrics for this project, illustrating improvements in both productivity and efficiency. The average time to iterate went from 4.8 h before to 3.1 h after a reduction of 35% (pre-intervention: $M = 4.80$ h, $SD = 1.22$; post-intervention: $M = 3.13$ h, $SD = 0.92$; $t(71) = 9.80$, $p < 0.001$, $d = 1.154$). As shown, adaptive task sequencing combined with AI-supported ideation reduces cognitive load and time spent on many exploratory dead ends.

In addition, the number of design variations created per concept increased 2.7-fold. Although the number of variations increased, quality did not decrease, as indicated by the improvements shown in Fig. 6. More importantly, G-DALE enabled students to create more versions in less time, leading to greater potential for deeper stylistic iterations in their work due to quicker cycles of divergence-convergence.

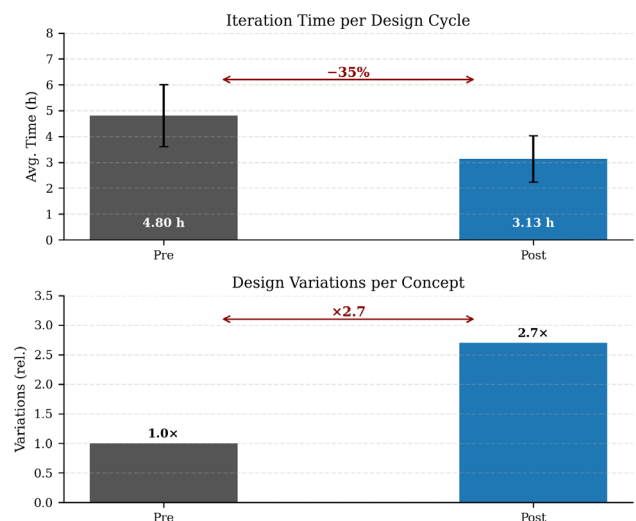


Fig. 6. Efficiency and productivity in AI-assisted design tasks.

These improvements align with findings from earlier

research on multimodal generative systems. However, these findings further demonstrate the importance of pedagogical structure in helping learners use generative systems effectively. Without structured guidance, generative models typically overwhelm learners with an excessive number of options. Nevertheless, by adapting prompting systems, students can explore generative innovations coherently.

C. Adaptive Personalization Patterns

Adaptive personalization patterns group students according to how they interacted with the adaptive mechanism. To create adaptive personalization patterns for each student, we performed hierarchical cluster analysis on z-score-standardized adaptive indicators (Adapt_Difficulty, Adapt_Refinement, Adapt_Style) using Ward's minimum-variance linkage (Euclidean distance). Cluster validity was confirmed by a cophenetic correlation of $r=0.970$ and a silhouette coefficient of 0.814 (Cluster A: 0.798; B: 0.804; C: 0.840). Between-cluster differences were significant for all three indicators (all $F > 400$, $p < 0.001$); Table 3 presents the descriptive statistics.

Table 3. Adaptive personalization indicator means and standard deviations by cluster ($n = 24$ per cluster)

Adaptive Indicator	Cluster A ($n = 24$)	Cluster B ($n = 24$)	Cluster C ($n = 24$)
Adapt_Difficulty	0.609 (0.025)	0.406 (0.022)	0.262 (0.027)
Adapt_Refinement	0.566 (0.031)	0.707 (0.027)	0.462 (0.027)
Adapt_Style	0.403 (0.019)	0.539 (0.027)	0.709 (0.030)

Fig. 7 illustrates how frequently refinement suggestions were used as an adaptive intervention, confirming previous findings indicating that learners relied heavily on AI micro-corrections during the mid-design process. The dendrogram shows three types of adaptive profiles: Cluster A: Students requiring high-level difficulty adjustments and moderate levels of refinement; Cluster B: Students requiring low-level difficulty adjustments and high levels of refinement; Cluster C: Students requiring minimal refinements and a high prevalence of style adjustment patterns. Students in Cluster C exhibited the highest Adapt_Style alignment ($M=0.709$) combined with the lowest Adapt_Difficulty frequency ($M=0.262$), suggesting that these learners possessed sufficiently stable aesthetic identities to engage with AI suggestions selectively. This pattern may reflect adaptive capacity—the strategic use of AI tools in ways that reinforce rather than displace individual creative logic [22]. Because we did not collect qualitative behavioral data, this interpretation remains tentative and warrants investigation in future research.

The heat map illustrates how frequently refinement suggestions were used as an adaptive intervention, confirming previous findings indicating that learners relied heavily on AI micro-corrections during the mid-design process. In contrast, within Cluster C, style interventions were more pronounced, indicating that students had established strong aesthetic identities and required alignment versus structural corrections. In conclusion, the presence of these learner groups confirms that the G-DALE adaptive engine is attuned to subtle behavioral indicators. Rather than providing uniform support, the adaptive mechanism differentiates among learners requiring cognitive scaffolding, stylistic calibration, and strategic redirection. Therefore, the evidence supports incorporating dynamic, AI-driven

personalization into design education rather than relying on static assistance [23].

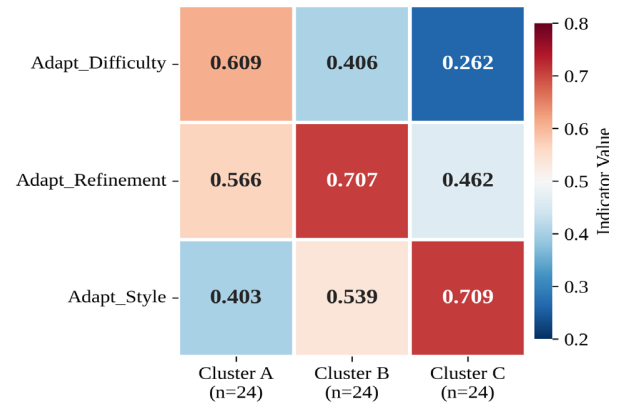


Fig. 7. Adaptive personalization clusters and adaptation intensities.

D. Learner Perceptions and Engagement

Using a Likert-based measure, Fig. 8 demonstrates that learners overwhelmingly perceive the benefits of G-DALE: 82% agreed or strongly agreed that G-DALE increased the clarity of their creative choices; 76% said they have greater confidence to explore; 71% reported that they were more aware of their own design tendencies. These statistics correlate with the cognitive and behavioral data reported in Figs. 5–7, and support the premise that structured generative assistance supports rather than reduces creative freedom.

However, the data also reveal learner concerns regarding G-DALE, as indicated by 24% of learners collectively reporting concern about being overly reliant on AI, and 18% reporting instances of generated style that differed from their intended styles. This discrepancy between generated and intended styles supports the need for continual oversight of the human (designer) inputs while developing a pedagogical approach that is transparent to all users.

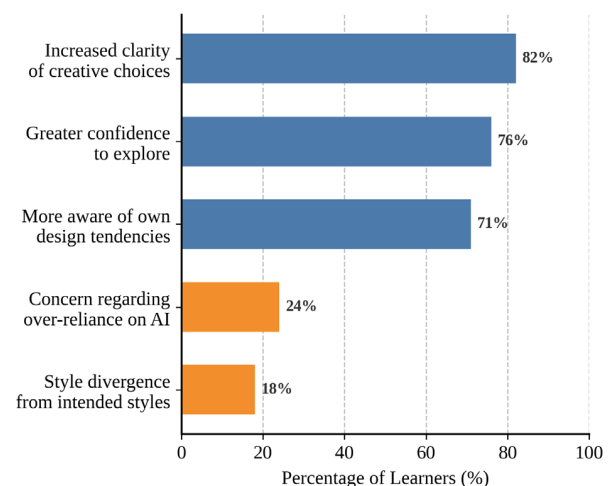


Fig. 8. Learner perceptions of AI-assisted personalized design learning.

The analysis of trends in learner perception suggests that G-DALE effectively bridged the gap between automated action and creative control for learners. Therefore, educators should view AI not as a replacement for personal expression but as a partner in the design process that reflects learners' personal histories and behaviors, consistent with the G-DALE framework's theoretical basis. Realism is warranted here: short-term novelty effects may have

contributed to elevated engagement, and a four-week snapshot cannot guarantee sustained motivation in extended implementations. There is a fine line between AI as an “educational agent” and AI as a “creative shortcut,” and maintaining that balance remains a core challenge for long-term curriculum design.

The findings also provide several broader implications for design education. First, the results indicate that structured generative support can enhance both conceptual and stylistic development, rather than only accelerating idea generation. This finding extends prior studies that primarily emphasized ideation speed without examining coherence in design reasoning. Second, the adaptive clustering results suggest that personalization emerges through differentiated support strategies, highlighting the importance of flexible instructional design when integrating generative tools.

However, several limitations warrant acknowledgment. The intervention lasted four weeks, which restricts conclusions about long-term creative development. The participant group consisted mainly of art and design students, which may limit generalization to other disciplines. In addition, the analysis relied primarily on performance metrics and did not explore qualitative insights into student reasoning in depth.

Future research could examine longitudinal implementations of adaptive generative learning, as well as applications in related creative domains such as multimedia production or architecture. Further work may also investigate hybrid feedback models that combine instructor critique with AI-generated guidance, particularly to address issues related to creative ownership and reliance on automated suggestions.

V. CONCLUSION

The G-DALE framework is a new way to use GAI in design education. We tested the G-DALE framework with design education students; the results showed increased creativity, reduced time to produce graphics, and greater student involvement. In addition, students created higher-quality design concepts, developed more consistent visual artwork, and finished their graphic design assignments more quickly because of G-DALE. The adaptive capabilities of G-DALE enabled students to receive assistance tailored to their specific learning styles and personal preferences. Students develop in diverse ways, as shown by the multiple distinct learning profiles identified through the research process. Most participants reported that AI guidance improved their clarity and confidence in design, while a minority expressed concerns about potential overreliance on AI.

In summary, the research demonstrated that the G-DALE framework provides a robust approach to harnessing generative AI as an educational tool. Pedagogically structured frameworks are critical to enabling students to develop enhanced creative capacity. Future research on G-DALE could extend the framework to other creative disciplines and explore additional generative AI-based educational tools and resources.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

G.O. conducted the primary research, developed the G-DALE framework, and drafted the initial manuscript; S.A. supervised the pedagogical design and provided critical revisions to the theoretical framework; U.K. designed the experimental study, performed the statistical analysis, and coordinated the submission process; S.B. managed the data collection during the four-week course and assisted in creating the instructional materials. All authors have read and approved the final version of the manuscript.

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