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An AI Integrated Design Thinking Model for Fashion Design Ideation in Vocational Education Using a Design Based Research Approach

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Abstract

The integration of generative artificial intelligence into creative education offers novel opportunities to enhance ideation, yet structured pedagogical frameworks for its application remain sparse. This study evaluates an innovative, theory-informed AI-integrated design thinking model that positions generative AI as a cognitive collaborator to facilitate structured ideation and technical translation in fashion design. Employing a Design-Based Research approach, a four-hour intensive workshop titled "*From Prompt to Pattern*" was implemented with undergraduate fashion design students (N = 30) at a vocational institution. Data collection utilised a mixed-method approach comprising pre- and post-intervention artefact evaluations, a post-workshop questionnaire based on the Technology Acceptance Model, and qualitative student reflections. Quantitative results confirmed high technology acceptance across Perceived Usefulness and Perceived Ease of Use, with emotional engagement acting as the strongest predictor of future behavioural intention. Empirical artefact analysis revealed a significant qualitative transformation from conventional, linear pre-workshop concepts to structurally complex, culturally integrated post-workshop outputs. The study demonstrates that embedding generative AI within a scaffolded pedagogical

framework enhances divergent thinking and creative self-efficacy without undermining human authorship, offering a scalable model for modern digital design curricula.

Keywords: Generative Artificial Intelligence, Fashion Design Education, Design Thinking, Technology Acceptance Model, AI Supported Learning, Vocational Education.

1. Introduction and Related Literature

1.1 AI-Supported Creativity in Design Education and Creative Learning Processes

Generative Artificial Intelligence (AI) is increasingly adopted in creative fields to generate visual and textual content from multimodal inputs (Chen et al., 2023; Guo et al., 2023). In design, these technologies support rapid idea generation, visualisation, and exploration, offering opportunities to enhance the creative process (Jalil, 2025). Focusing on students transitioning into content creators, Hwang and Wu (2025) discussed methods of design education that utilise generative AI and emphasised the emerging need for AI visual literacy skills. Similarly, Li and Balinas (2025) explored the applications, impacts, and pedagogical shifts associated with generative AI in information literacy design education and personalised learning. Lessons from the field highlighted by Tellez (2025) further underscore the need to integrate generative AI into design education to systematically assess its impact on creativity, pedagogical practices, and learning outcomes. Conversely, critical perspectives on AI imaginaries and creative labour in media production challenge uncritical adoption; Chow and Bueno (2025) critiqued the frequent use of "creativity" to justify the automation of creative work, arguing instead for the re-materialisation of human creative labour. To successfully integrate AI into contemporary design classrooms, Lee and Suh (2024) stated that educators must organise traditional design practical learning tasks within an explicit AI framework, thereby embedding AI into existing pedagogical models. By actively practising with AI technologies, students can develop the competence to synthesise diverse information sources and generate creative solutions in fashion design, preparing them to become future industry experts (Lee & Suh, 2024). Research indicates that AI technologies can optimise educational strategies by boosting students' creativity, critical thinking, and productivity through iterative idea generation and time-saving processes (Lee, 2024; Tomic et al., 2023). Moreover, AI-powered environments offer unique opportunities for collaboration, immediate feedback, and personalised learning (Tzirides et al., 2024). However, substantial concerns persist regarding ethical implementation, student over-dependence on algorithmic outputs, and the long-term impact on organic human creativity in the classroom (Kim, 2024). Although generative AI demonstrates significant educational potential, its systematic integration into fashion design pedagogy remains fragmented and under-theorised.

1.2 Design Thinking in Fashion Education

AI-assisted design approaches demonstrate how computational systems can be effectively applied to early-stage design workflows (Lee et al., 2021; Yan et al., 2022). Recent studies in fashion education emphasise regenerative design, socio-ecological thinking, and the need to challenge traditional designer-centric creative practices through emerging technologies and performative approaches (Ditmar et al., 2025; Park, 2025). Within the realm of fashion design, AI has been applied to automated design generation, style recommendation, and visual prototyping, enhancing designers' abilities to explore and innovate through prompt engineering (Cheng et al., 2022; De Lima, 2025). Prompt engineering, the process of translating design intentions into structured inputs that guide AI outputs (Bach et al., 2022; Ekin, 2023), aligns closely with design thinking by supporting iterative exploration, evaluation, and refinement (Jalil, 2025). In educational contexts, two primary avenues for working with AI have emerged. The first involves directly engaging students in the backend creation of AI technologies, such as building and curation of training datasets (Jalil, 2025). The second avenue focuses on training students to utilise AI as a fundamental tool within existing educational programs (An et al., 2023). Such AI-integrated programs can help students cultivate core competencies relevant to the global design industry, ultimately making them more marketable (Lee, 2025). Beyond the ideation phase, generative AI has been shown to improve student engagement, customise the learning process, and enhance capacity for instructional assessment planning (Tzirides et al., 2024). Moreover, as noted by Jony and Hamim (2024), AI-powered tools facilitate collaborative learning by organising group activities, encouraging equitable engagement, and enabling real-time co-creation unconstrained by geographical or physical limitations.

A predictive correlational study found a significant relationship between educators' use of AI technologies and their professional adaptability skills, suggesting that AI can support more innovative and flexible teaching practices (Dere & Dogan, 2025). Similarly, Kaskaya and Ates (2025) demonstrated that AI-supported visualisation tools enhance students' confidence, engagement, and continuity during complex creative tasks. These findings reinforce AI's role as a facilitator of creative exploration and cognitive flexibility in educational contexts. Despite these benefits, integrating AI into education presents several pedagogical and cognitive challenges. Kaplan et al. (2026) found that while generative AI can foster positive learning dispositions, it may also induce negative effects such as cognitive fatigue and reduced engagement in non-AI tasks, underscoring the need for guided, balanced instructional approaches. Similarly, Pratiwi et al. (2025) reported that excessive reliance on AI may lead to severe technological dependency, particularly among students with lower intrinsic motivation or limited access to resources. These insights suggest that structured pedagogical integration

is essential to ensure that AI supports, rather than undermines, meaningful learning processes. Finally, because most current research relies on self-reported data, which are subject to response bias, scholars recommend integrating more objective, qualitative measures to capture students' actual engagement and experiential learning accurately (Kaplan et al., 2026; Le et al., 2025). This highlights an urgent need for empirically grounded, context-specific studies. In this framework, generative AI is positioned not as a replacement for human agency but as a cognitive collaborator that supports designers during ideation, visualisation, reflection, and iterative exploration.

1.3 Technology Acceptance in AI-Supported Learning and Theoretical Limitations

Research on technology adoption indicates that factors such as social influence, perceived usefulness, and trust play a decisive role in shaping users' acceptance of generative AI. Studies using the Unified Theory of Acceptance and Use of Technology (UTAUT) demonstrate that these factors significantly influence both behavioural intention and actual use among students and instructors (Han & Kharuddin, 2025; Trung et al., 2025). However, such studies are predominantly conducted within non-design disciplines, leaving a gap in creative education contexts like fashion design. Furthermore, existing technology integration models, such as the Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006), emphasise the generalised interaction among technology, pedagogy, and subject-matter expertise but lack domain-specific creative execution. Similarly, research on AI-assisted design frameworks has focused tightly on computational design systems, generative design algorithms, and professional workflows (Chen et al., 2023; Wu & Li, 2025; Yan et al., 2022).

As outlined in Table 1, most of these frameworks assume advanced technical expertise and fail to provide the pedagogical scaffolding novice learners need. Consequently, limited research has systematically examined how generative AI can be pedagogically embedded in a structured fashion for design ideation within vocational education. While frameworks like TPACK and Creativity Support Systems (Shneiderman, 2007) offer valuable insights into technology integration and creativity enhancement, they do not sufficiently address human-AI co-creativity, design-thinking pedagogy, or measurable learning outcomes in fashion education. The comparison in Table 1 highlights that no current framework fully addresses the pedagogical integration of generative AI within design education. Hence, this study contributes a theory-informed AI-Integrated Design Thinking Model for fashion design education and provides empirical evidence of its effectiveness through a Design-Based Research (DBR) approach.

Table 1. Comparison of Existing Frameworks and the Proposed AI-Integrated EdTech Model

Framework	Primary Focus	Role of AI/Technology	Educational Orientation	Limitations	Contribution of the Proposed Model
TPACK	Integration of technology, pedagogy, and content knowledge	Technology as a teaching support tool	Strong pedagogical foundation	Does not specify creative design processes or AI ideation	Extends TPACK by embedding generative AI within design thinking stages
AI-Assisted Design Frameworks	Computational design and AI-generated outputs	AI as a design generator or algorithmic design assistant	Focused on professional design workflows	Limited pedagogical structure for student learning	Repositions AI as a cognitive design partner within educational design processes
Creativity Support Systems (CSS)	Enhancing human creativity through computational tools	AI as an ideation support and exploration tool	Weak pedagogical integration	Often tool-centred rather than learning-centred	Integrates AI-based creativity tools with structured design thinking pedagogy
Proposed AI-Integrated EdTech Model	AI-supported fashion design ideation in education	AI as a cognitive collaborator supporting ideation	Strong pedagogical integration using design thinking and TAM	Requires empirical validation across contexts	-

1.4 Conceptual Framework Development

There remains a definitive lack of empirically validated models that connect AI-supported ideation with structured design processes and measurable learning outcomes in design education. The model proposed by this study, illustrated in Figure 1, addresses this gap by grounding itself in design thinking pedagogy, human-AI collaboration theory, creativity support systems, and the Technology Acceptance Model (TAM). Developed through a DBR approach (Brown, 1992), the framework leverages design thinking theory to support the iterative, creative problem-solving required in fashion education. Within this model, generative AI functions as a cognitive collaborator that expands students' divergent thinking, visual ideation, and exploratory capabilities without replacing human creative agency.

Creativity is thus positioned as a co-constructive synthesis of human judgment and algorithmic exploration.

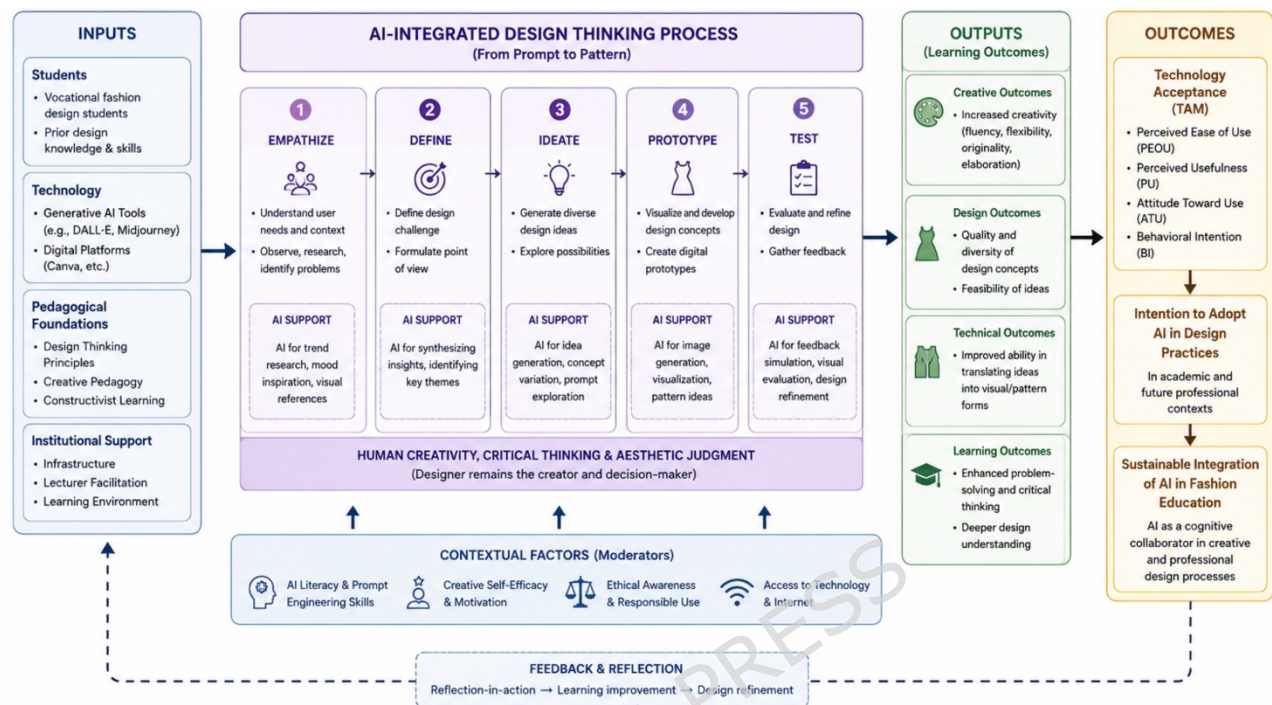


Figure 1. Conceptual Framework of AI-Integrated EdTech Design Thinking Model for Fashion Ideation

The development of the model involved systematically mapping specific AI functionalities, such as prompt-based visual generation and rapid iteration, to corresponding pedagogical activities across the five established stages of design thinking: *Empathise*, *Define*, *Ideate*, *Prototype*, and *Test*. To ensure alignment between theory and practice, the model integrates explicit learning objectives (creative ideation, technical translation, and AI literacy), targeted teaching methods (AI-augmented workshops and design sprints), and industry-relevant learning content (cultural references and sustainability themes). Rather than utilising generative AI as a standalone automated tool, this framework embeds technology within a macro-pedagogical structure. This structural containment prevents prompt fatigue and random output dependency by requiring students to maintain explicit creative intentionality. While AI acts as a computational catalyst during divergent ideation phases, traditional flat-pattern drafting and material reasoning govern the convergent, physical prototyping stages. To assess the operational efficacy of this ecosystem, TAM (Davis, 1989) is embedded as an analytical layer to map how students' psychological perceptions of utility and usability determine their long-term intention to adopt AI in professional practice. This study investigates three main research questions: How does the AI-Integrated Design Thinking

Model influence fashion design ideation? How do students perceive generative AI as a cognitive design collaborator? What factors influence students' acceptance of AI-supported design learning environments?

2. Methodology

2.1 Research Design

This study adopted a DBR approach to conceptualise, implement, and iteratively refine an AI-integrated educational model for fashion design ideation. Traditional experimental methodologies often isolate educational variables, failing to capture the systemic complexities of creative studio environments. In contrast, DBR was selected as the optimal research design for four distinct reasons. Firstly, it allows for the direct evaluation of technological interventions within authentic classroom settings, preserving the social and environmental dynamics of vocational training. Secondly, it supports the development of a structured, theory-driven pedagogical intervention (*From Prompt to Pattern workshop*) specifically designed to address a critical learning gap: translating abstract AI outputs into physically feasible garment designs. Third, the research configuration enables real-time observation and iterative adjustments to the instructional scaffold based on immediate student-tool interactions. Finally, it generates transferable theoretical insights regarding human-AI collaboration while simultaneously offering a practically refined, field-tested instructional model ready for curricular integration. Hence, the study consisted of two interdependent stages: the execution of the AI-enhanced fashion design workshop and the subsequent evaluation of the student learning experience and technology acceptance as measured by TAM.

2.2 Participants

The study was conducted at a public vocational education institution in Sarawak, Malaysia, specialising in technical creative industries. A purposive sampling technique was employed to select participants with the foundational technical design competencies required to execute the physical prototyping phase of the workshop, ensuring that the garments could be evaluated architecturally. The cohort comprised thirty third-year undergraduate students in a Bachelor of Design program. The gender distribution was 23 female students (76.7%) and 7 male students (23.3%), with an age range spanning 20 to 22 years old ($M = 21.2$, $SD = 0.64$). Baseline profiling indicated that all participants had no formal academic training in generative AI, prompt engineering, or algorithmic design workflows. However, 73% ($N = 22$) reported familiarity with consumer-tier mobile text-to-image applications for recreational purposes.

Formal ethical clearance was obtained from the institutional research ethics committee before launch. All participants were provided with comprehensive disclosure documentation and signed informed consent forms granting permission to analyse their survey responses and design artefacts. To protect academic integrity and establish responsible AI boundaries, students attended a mandatory 15-minute briefing detailing the mechanics of algorithmic plagiarism, data bias, and stylistic appropriation. The guidelines explicitly mandated that AI could be used only for divergent conceptual support, establishing that final technical layouts, structural specifications, and pattern mappings remained the exclusive intellectual property of the student designer.

2.3 Workshop Design and Procedure

The proposed model and its instructional guide were implemented during an intensive, four-hour in-class learning exercise titled *"From Prompt to Pattern."* The primary objective of the workshop was to bridge the pedagogical gap between AI-generated visual concepts and technically feasible fashion designs. To achieve this, the workshop was organised into four consecutive phases that combined digital AI exploration with traditional design practice. The workshop structure is mapped directly to the design thinking milestones, as detailed in Figure 2 below.

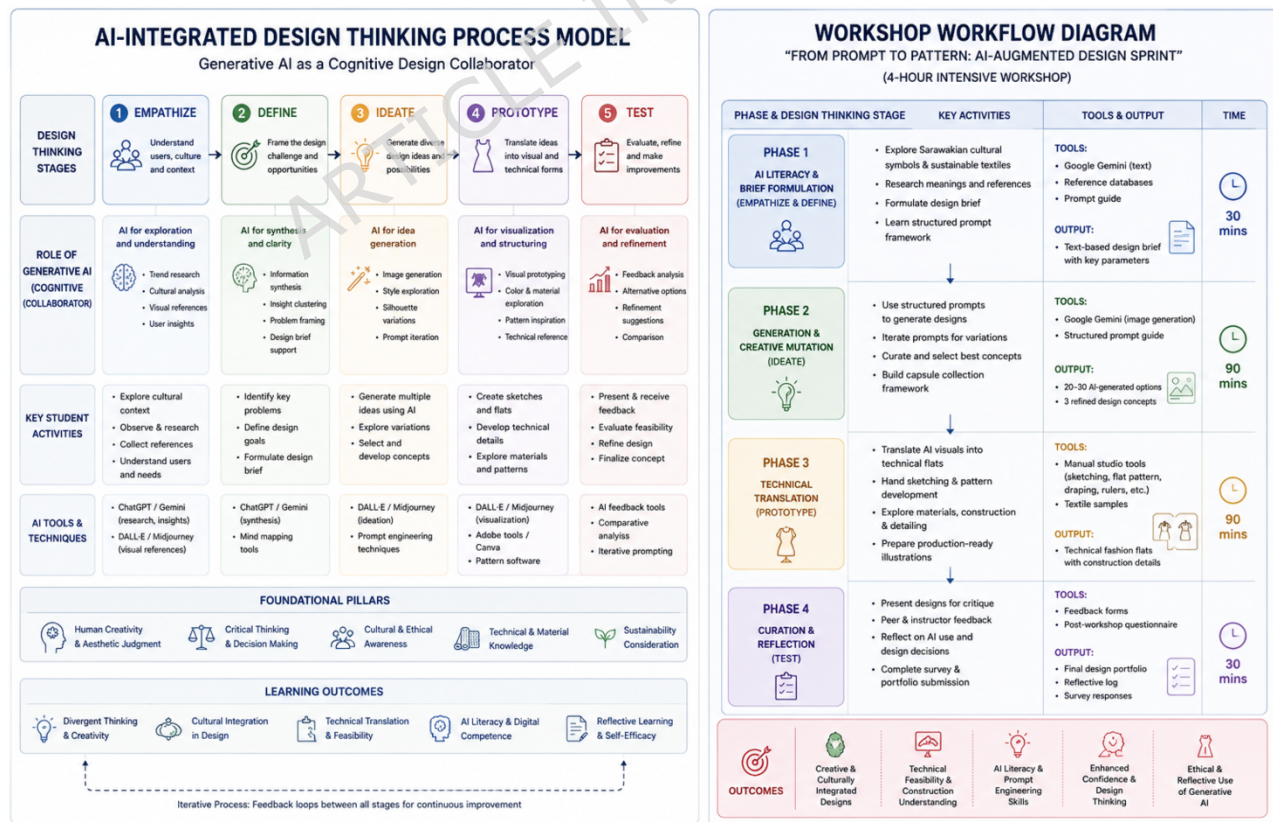


Figure 2. Workshop Workflow Diagram (right) based on AI-Integrated Design Thinking Process Model (left)

Phase 1: AI Literacy and Prompt Engineering. The instructor delivered a targeted tutorial focusing on the mechanics of text-to-image generation, the role of large language models as cognitive design partners, and the avoidance of biased or repetitive outputs. Students were introduced to a structured prompt architecture consisting of four core components: garment type, cultural theme reference, materiality property, and aesthetic style filter.

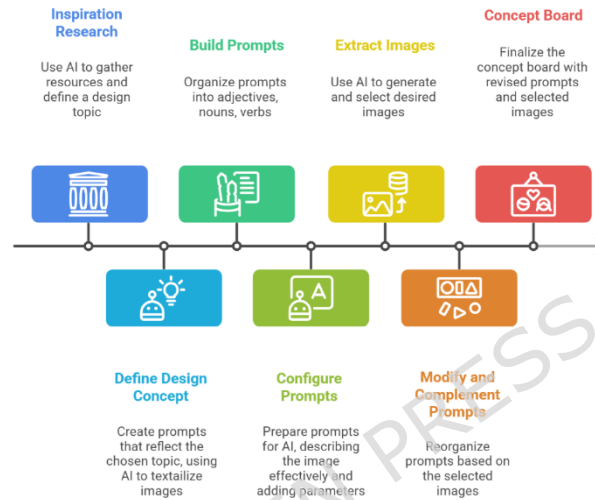


Figure 3. AI-Assisted Design Inspiration and Prompt-Based Ideation Process

Phase 2: Idea Generation and Innovation. According to Figure 3, Students engaged with the design challenge of modernising traditional Sarawakian ethnic motifs) into festival garments. Using the structured prompt guides, students iteratively modified prompts, generating an initial pool of 20-30 visual variants. Students then engaged in convergent filtering, evaluating the AI outputs against historical authenticity and production viability, narrowing their pool down to three anchor concepts.

Phase 3: Digital-to-Physical Translation. Students transitioned away from the digital interface to resolve structural realities, as shown in Figure 4. Using the three selected AI visual concepts as references, students executed manual flat sketches and production flats. This phase required students to decode the AI-generated, ambiguous, fluid textures into precise physical values, explicitly mapping pattern grain lines, seam allowances, structural closures (zippers, buttons), and exact material draping configurations.

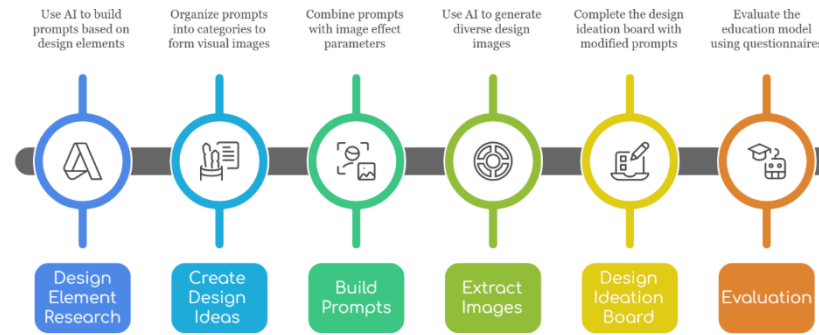


Figure 4. AI-Driven Design Idea Generation Process

Phase 4: Reflection. The final phase focused on peer testing and administrative evaluation. Students mounted their completed ideation boards, displaying their pre-workshop concepts, intermediate AI prompt iterations, final AI renders, and finalised technical production flats, for collective review. Students then completed the quantitative evaluation survey and submitted their individual qualitative reflective logs.

2.4 Generative AI Tools and Prompt Guide

Google Gemini was deployed as the exclusive generative engine for this intervention due to its cross-platform accessibility within institutional computing labs, rapid iteration cycles, and high accuracy in processing complex, multi-layered textual prompts. To prevent students from generating random, unguided images, a mandatory *Prompt Engineering Scaffolding Guide* was developed based on professional computational design workflows (Ekin, 2023). The guide focused on key fashion design elements, including motif development, silhouette exploration, material interpretation, and sustainability considerations, tailored to the workshop theme: a fashion design collection for the “Sarawak Rainforest Festival 2026.” The guide enforced a rigid syntax structure: = Core Garment Archetype + Specific Sarawak Iconography + Textile Materiality Specification + Structural Closure/Drape Detail + Aesthetic Style Constraint.

2.5 Data Collection

Data collection leveraged a concurrent mixed-methods design. For the quantitative survey, a 22-item post-workshop instrument was adapted from Davis’s (1989). Items were scored on a 5-point Likert scale (1 = Strongly Disagree; 5 = Strongly Agree), measuring Perceived Usefulness (3 items), Perceived Ease of Use (3 items), Attitude Toward Use (3 items), Behavioural Intention (3 items), and specific design thinking phase perceptions (10 items). Students completed an open-ended qualitative journal entry immediately following the critique session. Throughout the four-hour session, the researchers functioned as non-participant observers, documenting behaviour via a standardised Observation Protocol

Sheet. Pre-workshop design sketches (produced by the same cohort during a standard classroom project the previous week) and post-workshop portfolio submissions were assessed blind by an external panel of three veteran fashion design educators. The artifacts were completely stripped of participant markers and evaluated against a standardized 4-dimensional matrix (scored 1 to 5 per dimension): variation in silhouettes, construction archetypes, and form experimentation, sophistication of the overarching artistic narrative and thematic development, the maturity with which traditional Sarawakian symbols were hybridized into modern garments without lapsing into superficial stereotyping and the real-world structural viability of the flat drafts, pattern logic, seam calls, and draping descriptions.

2.6 Data Analysis

Quantitative analysis was performed using IBM SPSS Statistics 29. Descriptive statistics were computed for the mean and standard deviation for all constructs. Internal reliability was established via Cronbach's alpha. Relational dynamics were mapped using Pearson's Product-Moment Correlation and stepwise linear regression to establish predictive pathways among TAM variables. A one-way ANOVA with post hoc Tukey HSD tests was used to evaluate differences in Perceived Usefulness across varying user-ease-of-use thresholds. For the qualitative analysis, a reflective log was subjected to inductive thematic analysis following Braun and Clarke's (2006) framework. Two independent coders resolved discrepancies through consensus, yielding structural themes surrounding human-AI creative tension, prompt mechanics, and technical translation barriers. Finally, the qualitative thematic matrices were triangulated directly alongside the quantitative TAM outputs to assess convergence or divergence between student perceptions and actual artefact performance.

3. Results and Findings

3.1 Implementation of the AI-Integrated Design Thinking Model (RQ1)

To address RQ1 (*How does the AI-Integrated Design Thinking Model influence fashion design ideation?*), the proposed framework was evaluated as a design-based intervention during the intensive workshop. The model systematically structured student activities and cognitive processes across five distinct pedagogical stages:

- *Empathise*: Students leveraged generative AI tools to unpack complex cultural references and user contexts, which significantly expanded the scope of their initial thematic research.

- *Define*: AI-supported synthesis enabled students to cross-reference historical data, allowing them to formulate clearer design problems and highly structured design briefs.
 - *Ideate*: This stage demonstrated the most pronounced algorithmic impact. Generative AI enabled rapid, friction-free exploration of multiple design alternatives, thereby driving divergent thinking.
 - *Prototype*: Students translated abstract, fluid AI-generated visuals into concrete technical fashion sketches, successfully bridging the gap between conceptual imagination and practical design execution.
 - *Test*: This final stage supported critical, reflective evaluation. Students objectively assessed both the AI-generated outputs and their own downstream design modifications.
- Overall, these observations indicate that the model successfully organised the creative workflow, converting what is often an erratic creative process into a structured, measurable learning experience.



Figure 5. Design transformation across the AI-integrated workshop: (a) pre-workshop design outputs showing conventional and limited ideation; (b) workshop activities; (c) post-

workshop design outcomes demonstrating enhanced creativity, cultural integration, and design complexity

To objectively measure how integrating generative AI into this structured framework influenced physical design outputs, a comparative analysis was conducted on student portfolios compiled before, during, and after the workshop. The external panel evaluated the 30-student artefact sets against four core criteria: design diversity, conceptual depth, cultural hybridisation, and technical viability. The visual and structural analysis revealed distinct transformations across the three operational phases:

Pre-Workshop Design Outputs (Figure 5a): Baseline artefacts exhibited highly linear, conventional ideation patterns. The initial sketches relied heavily on predictable resort-wear silhouettes, basic surface pigmentation, and minimal textile or structural exploration.

AI-Augmented Workshop Activities (Figure 5b): During the active technological intervention, students shifted away from safe, singular concepts to engage in rapid visual variation. Guided by the strict syntax parameters of the *Prompt Engineering Scaffolding Guide*, they explored an expansive array of complex textile textures, avant-garde drapes, and non-traditional geometric panel distributions.

Post-Workshop Design Outcomes (Figure 5c): Final portfolio submissions demonstrated substantial advancements in creative complexity and conceptual maturity. The final garments displayed sophisticated fabric layering, deliberate asymmetry, and a deep, authentic hybridisation of traditional Sarawakian *Pua Kumbu* motifs into contemporary silhouettes. The post-workshop portfolio artefacts confirmed that students did not merely replicate or passively accept the raw algorithmic outputs. Instead, they actively translated fluid digital generations into precise, production-ready flat fashion sketches. The final drawings contained comprehensive annotations detailing pattern grain lines, seam allowances, structural hardware closures, and physical textile weights. This definitive evolution demonstrates that the AI-Integrated Design Thinking Model effectively scaffolds both divergent conceptual exploration and convergent technical execution.

3.2 Perceived Impact on Soft Skills Development (RQ2)

To address RQ2 (*How do students perceive generative AI as a cognitive design collaborator?*), although participants had prior training in fashion design, their formal knowledge of generative AI varied. A significant majority reported prior hands-on experience with AI text-to-image tools, indicating a high degree of non-academic digital familiarity. The findings presented in Table 2 demonstrate that the fashion design ideation, the learning experience

throughout the stages of design thinking, and the students' perceived learning outcomes have been positively affected by the AI-integrated EdTech model.

Table 2. Perceptions of AI in Fashion Design Education and Creation

Construct	Survey Item	Mean	SD
Generative AI as a Cognitive Design Catalyst	Generative AI supported my creative thinking during fashion design ideation, especially in culturally inspired and ethnic costume design.	4.25	0.51
	AI tools helped me explore design ideas that I would not have considered otherwise.	4.38	0.49
	Using AI enhanced my ability to conceptualise fashion designs visually.	4.05	0.64
	AI functioned as a creative collaborator rather than replacing my own design thinking.	3.92	0.73
Empathise Stage (Design Thinking)	AI-assisted resources helped me better understand users' needs and preferences.	3.71	0.81
	AI tools supported my exploration of cultural and contextual fashion references.	4.6	0.50
	The Empathise stage helped me develop more meaningful fashion design concepts.	4.7	0.47
Define Stage (Design Thinking)	AI tools helped me synthesise research information into clear design directions.	4.7	0.47
	I was able to define fashion design problems more clearly with AI assistance.	4.4	0.58
	AI-supported ideation improved the clarity of my design brief.	4.3	0.61
Ideate Stage (Design Thinking)	Generative AI enabled me to generate a wide range of fashion design ideas.	4.1	0.66
	AI-supported ideation encouraged me to think beyond conventional approaches to fashion design.	4.0	0.72
	AI tools helped me experiment with different silhouettes, motifs, and colour schemes.	3.9	0.79
	The Ideate stage significantly expanded my creative possibilities.	4.5	0.51
Prototype Stage (Design Thinking)	I was able to translate AI-generated visuals into technical fashion sketches.	4.25	0.64
	AI-generated ideas were feasible for further development into fashion designs.	4.58	0.50
	This stage helped me better understand the structure and construction logic of garments.	4.05	0.71
Test Stage (Design Thinking)	Feedback during the testing stage helped me improve my design ideas.	4.6	0.50
	I was able to evaluate the strengths and limitations of AI-generated outputs critically.	3.92	0.68
	The reflection process improved my awareness of my own design decisions.	4.61	0.49
Learning Outcomes	I am more confident in generating fashion design ideas after the workshop.	4.21	0.59
	The workshop expanded my creative thinking abilities.	4.7	0.47
	I can better evaluate technical feasibility of fashion design ideas.	4.8	0.41
	I am more aware of the ethical and creative implications of using AI in fashion design.	3.8	0.85

Participants stressed that AI gave them further opportunities to develop a broader picture in their visual imagination, which was shaped by personal judgment and design intention. One student (no.7) mentioned: *"AI opinion helped me to see a lot of design possibilities quickly, but I still had to make a decision which thought is suitable for my concept."* Another student (no.12) explained: *"It was like a brainstorming idea with a partner. The AI helped it to provide ideas, but I was still controlling the direction of my design, I believe."* This indicated that the EdTech model infused with AI positively affected students' ideation in fashion design, their engagement during the design thinking process, and their perceived learning outcomes. In general, students have claimed that generative AI consistently supports creative exploration without replacing their role as active participants in the design process. Notably, students did not feel that AI would replace their own design thinking; instead, it was seen as a partner that expanded the range of ideation and maintained human creativity and authorship. The AI-based resources were efficient during the Empathise stage, enabling more effective exploration of cultural and contextual fashion references and the production of more meaningful design ideas.

Table 3. Emergent Qualitative Themes from Student Reflections

Theme	Description	Example Student Reflection
AI as a Cognitive Collaborator	Students perceived AI as a brainstorming partner rather than a replacement for creativity	"AI helped me explore many design ideas quickly, but I still controlled the final direction."
Expansion of Creative Exploration	AI encouraged divergent thinking and experimentation with new visual concepts	"The AI allowed me to explore design possibilities that I had never considered before."
Structured Ideation Through Prompting	Prompt guides helped students organise and refine their creative process	"The prompt structure made it easier to stay focused and generate meaningful ideas."
Human-Centred Decision Making	Students maintained ownership over design decisions and interpretation	"AI-generated ideas, but my own judgment determined what worked for the design."
Ethical Awareness and Cultural Sensitivity	Students reflected on originality, authorship, and cultural representation	"AI is useful, but we still need to think about originality and respecting cultural identity."
Technical Translation Challenges	Students recognised the need to convert AI visuals into feasible garments manually	"The AI image looked interesting, but translating it into a real garment required technical thinking."

As shown in Table 3, the qualitative findings reinforce the quantitative TAM results by demonstrating that students viewed generative AI as a supportive cognitive collaborator that enhanced ideation, creative exploration, and reflective learning. However, students also emphasised the continued importance of human judgment, cultural understanding, and technical fashion knowledge during the design process. The findings in the Define stage indicate that generative AI helped synthesise research data and explain well-defined design

issues and briefs. Students viewed generative AI as a useful cognitive assistance tool for ideation in fashion design. However, students also considered personal interpretation important; student fifteen stated that *"AI gave references, but knowledge of the culture still relied on my research and reflection."* In the Define stage, students demonstrated greater clarity in structuring design problems; student no. 11 mentioned that *"Using AI helped me to organise my ideas and to define clearly what my design problem was."* AI-assisted processes were said to help students organise their thoughts, narrow down design paths, and improve problem definition in fashion design.

The Ideate stage revealed that AI used divergent thinking. Students said generative AI helped them generate more ideas for fashion designs and allowed them to explore design forms beyond traditional ones. Although AI enhanced the exploration of visuals through silhouettes, motifs, and colour schemes, the most significant association with the expansion of creativity was the organisation of ideation rather than the unorganised creation of images. One student (no. 11) stated: *"The format of the workshop helped me to stay focused. The prompt guide made it easier to use AI effectively."* Students also increased in confidence and ownership of their work. Students (no. 24) believed that *"I felt more confident about making the decision because I felt like if I made a wrong decision, I could just check it quickly before making a proper decision."* These findings suggest that the EdTech ecosystem enabled active learning and increased learners' agency. Students showed greater awareness of the ethical aspects. One student (no. 20) had the following reflection: *"I learned that I should not rely too much on AI because it will not only impact my own creativity".* Another (no. 6) added: *"AI is useful and still needs to think about the authorship and originality in our designs."* These thoughts underscore the need to integrate ethics and AI literacy into fashion design education.

Table 4. User Perceptions of an AI-Integrated EdTech Model for Fashion Creation based on TAM

Survey Item	Mean (M)	Cronbach's Alpha (α)	Interpretation
<i>Perceived Usefulness (PU)</i>	4.59	.93	Students perceived AI as highly valuable for fashion ideation
Using AI improved my performance in fashion design ideation.	4.4		
AI tools enhanced the quality of my design ideas.	4.88		
AI-assisted ideation helped complete the design task.	4.5		
<i>Perceived Ease of Use (PEOU)</i>	4.66	.89	Students found AI tools accessible and easy to use
Learning to use the AI tools was easy for me.	4.78		
I found it easy to generate design ideas using AI.	4.7		
Interaction with the AI tools was clear and understandable.	4.5		

<i>Attitude Toward Use (ATU)</i>	4.30	.81	
I enjoyed using AI tools during the fashion design process.	4.6		Positive emotional engagement toward AI-supported learning
I have a positive attitude toward AI-assisted ideation for fashion design.	4.21		
Using AI made the design process more engaging.	4.08		
<i>Behavioural Intention (BI)</i>	4.44	.90	
I intend to use AI tools in future fashion design projects.	4.38		Strong intention to continue using AI in future projects
I would recommend AI-assisted design tools to other fashion design students.	4.44		
I am interested in further exploring AI in fashion design education.	4.5		

3.3 AI-Integrated EdTech model Verification (RQ3)

To address RQ3 (*What factors influence students' acceptance of AI-supported design learning environments?*), the general results in Table 4 indicate that acceptance of and an optimistic view of AI-based learning environments for fashion design are high. These results suggest that the EdTech model enhanced by AI demonstrates high sustainability in implementation outside the workshop. The results show that the proposed AI-based model successfully fostered the ideation process in fashion design by developing the most significant soft skills: digital, creative thinking, problem-solving, sustainability awareness, and communication. The TAM analysis has confirmed high acceptance, usability, and intention to use AI tools in future design practices among students. In addition, the results show a high level of PU, indicating that students viewed generative AI as having high cognitive design value for broadening fashion design ideation. High PEOU is further evidence that students worked well with AI tools during the ideation and prototyping phases, with no (or minimal) technical barriers. Positive ATU indicates student acceptance of AI-augmented teaching methods, and firm BI indicates a willingness to integrate AI methods into future fashion design projects. All TAM constructs demonstrated strong internal reliability, with Cronbach's alpha values ranging from 0.81 to 0.93, indicating satisfactory internal consistency (see Table 4).

3.3.1 Correlation Analysis

Pearson correlation analysis was conducted to examine relationships among TAM constructs. As shown in Table 5, all correlations were positive and statistically significant ($p < .01$). The strongest relationship was identified between ATU and BI, indicating that positive emotional engagement with AI-supported design activities strongly influenced students' intention to continue using AI technologies in future design practices.

Table 5. Pearson Correlations Among TAM Constructs, $**p < .01$ (2-tailed)

Constructs	PEOU	PU	ATU	BI
PEOU	1			

PU	.64**	1		
ATU	.58**	.71**	1	
BI	.55**	.69**	.76**	1

3.3.2 Stepwise Linear Regression Analysis

Regression analysis further confirmed the relationships among TAM constructs. PEOU significantly predicted PU ($\beta = .64$, $p < .001$), accounting for 41% of the variance. Both PU ($\beta = .53$) and PEOU ($\beta = .27$) significantly influenced ATU, accounting for 56% of the variance. ATU emerged as the strongest predictor of BI ($\beta = .59$), followed by PU ($\beta = .31$), accounting for 63% of the variance. These findings indicate that both usability and perceived creative value influence students' acceptance of AI tools, with emotional engagement playing a key role in future adoption. The small difference in effect size between ATU and BI, which is common in TAM research, is due to pragmatic factors, such as cost, institutional access, and long-term availability, rather than resistance to the technology itself.

3.3.3 Inferential Hypothesis Testing: One-Way ANOVA

To further examine the effect of PEOU on PU, a one-way ANOVA was conducted, grouping PEOU into low, medium, and high levels. The results indicated a statistically significant difference in PU across the three groups, $F(2, 27) = 12.84$, $p < .001$. Post hoc Tukey tests revealed that students with high PEOU reported significantly higher PU than those with medium or low PEOU, confirming the important role of ease of use in shaping perceptions of usefulness. These findings reinforce the significance of usability in AI-supported learning environments, suggesting that students are more likely to perceive generative AI as valuable when it is accessible and easy to use. Furthermore, the results indicate that experiential and affective responses, rather than purely functional aspects of the technology, play a key role in influencing students' intention to continue using generative AI in fashion design practice. The findings of the one-way ANOVA also provide evidence on the pivot position of ease of use in influencing adoption. Notable differences in PU among low, medium, and high PEOU groups ($p < .001$) provide evidence that students with fewer usability barriers found AI to be significantly more valuable for fashion design ideation. This observation highlights the value of a user-friendly EdTech model, in which embedded instructions, scaffolding prompts, and visual-based interfaces are given greater precedence than technical sophistication. Overall, the findings demonstrate that the proposed model was effective both as a pedagogical intervention and as a design-based framework, as evidenced by improvements in design outcomes, high levels of student engagement, and strong technology acceptance. Importantly, these findings confirm that the model's effectiveness extends beyond user perception.

The integration of generative AI into structured design thinking stages enabled students to move from linear ideation to iterative, exploratory design processes. This demonstrates that the model functions as an effective pedagogical intervention, improving both the process and outcomes of fashion design ideation. The effectiveness of the proposed model as a design-based intervention is evidenced through the observable transformation in students' design outputs. The comparison between pre- and post-workshop designs demonstrates measurable improvements in design diversity, conceptual depth, and technical translation. These changes indicate that the model not only enhanced students' perceptions of learning but also directly influenced their design performance and creative processes. This aligns with the principles of DBR, in which the success of an intervention is evaluated through both learning outcomes and the quality of the produced artefacts. As shown in Figure 5, a clear transformation is evident in students' design outputs, progressing from conventional pre-workshop designs to more complex, diverse, and conceptually rich post-workshop outcomes.

4. Discussion

The empirical findings of this study provide clear evidence of the structural and psychological dynamics that emerge when generative AI is integrated into vocational fashion design pedagogy. By evaluating both student design artefacts and TAM pathways, the results challenge the assumption that generative AI tools are merely technological novelties. Instead, the data support positioning generative AI as a structured cognitive design mediator that augments creative exploration, critical reflection, and technical translation within the design thinking pipeline.

4.1 AI as Cognitive Augmentation and Human-AI Co-Creativity

The significant qualitative leap observed between pre-workshop conventional designs (Figure 5a) and post-workshop structurally complex artefacts (Figure 5c) demonstrates the capacity of generative AI to support cognitive augmentation. The high descriptive scores for the Ideate phase ($M = 4.50$, $SD = 0.51$) confirm that students perceived the tool as an expansive mechanism for divergent exploration. Generative AI shifts the early-stage design bottleneck. In traditional workflows, students encounter cognitive friction when manually sketching multiple variations, often settling for a single linear solution prematurely. Algorithmic generation removes this mechanical constraint, allowing students to rapidly evaluate dozens of visual iterations (silhouettes, asymmetry, and layering) in real time. This finding extends the conclusions of Kaskaya and Ates (2025), who noted that computational visualisation tools increase creative self-efficacy and emotional investment during design tasks. It also aligns with Chen et al. (2023), confirming that generative models successfully widen the initial ideation space. The qualitative reflections (student no. 12) demonstrated that this configuration establishes true human-AI co-creativity; the AI functions as a fluid generator of

possibilities. At the same time, the human designer retains executive control as the authority for curation and selection.

4.2 Creativity Enhancement versus Dependency Risks in Pedagogy

A major concern within emerging educational technology research is the risk of student dependency, where over-reliance on automated tools might diminish critical thinking and problem-solving skills (Pratiwi et al., 2025). The structural breakdown of our design thinking stages provides clear insights into how structured scaffolding can mitigate these risks. Students achieved high levels of creative output because the AI interaction was explicitly constrained within successive pedagogical milestones (*Empathise, Define, Ideate, Prototype, Test*). In the *Define* stage, the AI was not used to sketch garments, but rather to organise text briefs and clarify project parameters. This structured sequence addresses the vulnerabilities identified by Kaplan et al. (2026), who warned that unguided AI exposure can cause cognitive fatigue and passive consumption. By forcing a dedicated Digital-to-Physical Technical Translation in Phase 3, the workshop disrupted potential automated dependency. Students were forced to evaluate the software's ambiguous visual outputs against real-world production constraints (grain lines, pattern seams, closures), ensuring that human critical thinking remained central to the workflow. The findings further suggest that AI literacy and prompt engineering should be recognised as emerging core competencies within future fashion and creative design curricula.

4.3 Prompt Literacy as a New Design Competency

The study highlights that in modern digital design curricula, prompt literacy must be recognised as a distinct, core design competency rather than a secondary technical skill. The quantitative data showed that the *Ideate* phase required clear constraints, which were directly supported by the implementation of our structural prompting guide. Prompt engineering represents a shift from manual execution to conceptual curation. The designer's primary tool is no longer just the marker or the draped fabric, but the articulation of design intent through highly precise, multi-variable textual matrices. This finding supports Acar (2025), who argued that modern digital literacy must be coupled with 21st-century competencies like analytical reasoning and problem-solving. When students constructed prompts using specified syntax (combining archetypes, cultural iconography, and textile types), they engaged in high-level design thinking. This syntax-driven approach aligns with Lee and Suh (2024), proving that for AI to be effective in the classroom, it must be integrated with traditional technical vocabulary and historical design parameters.

4.4 Theoretical and Ethical Implications

The one-way ANOVA results and post-hoc Tukey HSD tracking show that students who experienced low prompt friction (High PEOU) reported significantly higher utility metrics (PU).

In creative fields, if an interface requires excessive troubleshooting or produces random, uncontrollable variations, its perceived value for design drops immediately. The regression model revealed that Attitude Toward Use, representing emotional and creative engagement, was the single strongest direct predictor of future Behavioural Intention, outweighing purely functional utility. This validates the use of the TAM framework within studio-based environments, proving that long-term technology adoption among creative students depends heavily on maintaining an active sense of personal authorship and creative enjoyment during tool interactions. The lowest average score in the study was for student awareness of ethical and creative implications. This pattern highlights a critical ethical tension inside generative art education, particularly when working with localised or indigenous design elements. When prompted with terms like *"Sarawakian pua kumbu motifs,"* the generative engine quickly produces complex visual layouts. However, the software lacks an understanding of the sacred contexts, cultural lineages, or historical narratives embedded within those geometric weaves. The outcome shows that generative AI tools risk treating cultural identities as superficial design trends if used without guidance. Therefore, design programs must implement responsible AI guidelines. These guidelines should include strict requirements for historical cross-referencing, formal credit of indigenous design sources, and clear documentation of prompt heritages to maintain academic integrity and prevent automated cultural appropriation.

4.5 Limitations of the Study

The study was conducted with a purposive sample of thirty undergraduate fashion design students inside a single public vocational institution in Malaysia. Consequently, the quantitative and qualitative profiles may reflect specific institutional cultures and baseline skills, limiting immediate generalizability to alternative design disciplines or distinct international cohorts. The pedagogical intervention was executed as a four-hour intensive design sprint. This brief timeline makes it impossible to gather longitudinal data. It remains unclear whether the recorded creative benefits and high technology acceptance scores persist throughout an entire multi-semester production cycle or drop once students confront the realities of large-scale physical garment assembly. Because this workshop represented the participants' first formal, curriculum-guided exposure to generative prompt engineering, the satisfaction metrics and positive attitudes may be partially amplified by a novelty effect. The initial excitement of generating rapid digital assets can temporarily inflate user evaluations of ease and practical value. Current multimodal engines display a clear functional boundary: they lack material reasoning capabilities. The software can easily generate an innovative aesthetic drape, but it cannot calculate physical parameters such as fabric weight, warp/weft grain lines, seam allowances, or stitch behaviour. As a result, the tool remains effective

primarily during early conceptual ideation, requiring a complete reliance on traditional human expertise to achieve actual physical utility.

5. Conclusion

This study evaluated an AI-Integrated Design Thinking Model for fashion design ideation within vocational education using a DBR approach. The findings demonstrate that integrating generative AI within a structured pedagogical framework can enhance creative exploration, divergent thinking, and technical translation while preserving human-centred creativity and authorship. The implementation of the *"From Prompt to Pattern"* workshop showed that generative AI can effectively support students throughout the design thinking process, particularly in expanding ideation and facilitating exploratory design development. The study also revealed high levels of technology acceptance, with perceived ease of use and positive attitudes significantly influencing students' intention to adopt AI-supported design practices in future learning and professional contexts. These findings suggest that the educational value of generative AI depends not only on technological capabilities but also on pedagogical structure, critical reflection, and ethical guidance. Theoretically, this study contributes to the discourse on human-AI collaboration in creative education by positioning generative AI as a cognitive collaborator within design thinking pedagogy. The proposed model extends existing technology integration frameworks by connecting AI-supported ideation, creativity development, and technology acceptance within a unified educational approach. Practically, the study offers a scalable instructional framework for integrating AI literacy, prompt engineering, and creative design practices into contemporary fashion and vocational education curricula. Despite these contributions, the study was limited to a single workshop implementation involving a relatively small sample at a single vocational institution. Future research should investigate the long-term impact of AI-integrated design learning across broader educational contexts, extended studio environments, and interdisciplinary creative practices, including the integration of generative AI with advanced digital prototyping and 3D garment simulation technologies.

Declarations

Ethical Approval

This study received ethical approval from the Ethics Committee of the Faculty of Applied and Creative Arts, Universiti Malaysia Sarawak (UNIMAS). The research procedures were conducted in accordance with the ethical guidelines and regulations of Universiti Malaysia Sarawak and followed internationally accepted standards for research involving human participants.

Consent to Participate

Informed consent was obtained from all participants before they participated in the study. Participants were informed about the purpose of the research, and their participation was voluntary and anonymous.

Consent to Publish

Informed consent for publication of anonymised data and research findings was obtained from all participants involved in the study. Participants were informed that the collected data would be used for academic publication purposes.

Declaration of AI-Assisted Technologies in the Writing Process

During the preparation of this manuscript, the author used ChatGPT to assist with language refinement and text rephrasing. All generated content was carefully reviewed, edited, and verified by the authors, who take full responsibility for the final content of the publication.

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Author's contribution

MHJ - Conceptualisation; Methodology; Software; Formal Analysis; Investigation; Resources; Data curation; Writing Original draft; Visualisation and Project Administration. **JA** - Validation, Investigation, Resources, Data curation, Reviewing and Editing.

Data availability

The data is available upon request from the corresponding author.

Clinical trial number: Not applicable

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