

An Ai-Driven Framework for Personalized Fashion Design Generation and Customization

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DOI: <https://doi.org/10.51244/IJRSI.2026.1308000204>

Received: 31 August 2026; Accepted: 05 September 2026; Published: 15 September 2026

ABSTRACT

Artificial intelligence (AI) is increasingly used to accelerate ideation and visualization in fashion, yet empirical evidence on localized, education-oriented design systems remains limited. This study developed and evaluated Fashion Studio, an AI-driven framework that converts user prompts, sketches, style preferences, fabric selections, and body-related parameters into customizable fashion-design concepts. The framework was developed through a system development life-cycle process and organized around input, AI processing, customization, visualization, project management, and designer-client feedback modules. A descriptive-developmental evaluation was conducted at Palompon Institute of Technology during School Year 2025-2026. Thirty students and 10 faculty members (N = 40) assessed the system using a structured questionnaire adapted from ISO/IEC 25010 quality characteristics. Descriptive statistics summarized functional requirements, user familiarity, software acceptability, and open-ended feedback; group evaluations were compared at the .05 significance level. The user interface (M = 4.50) and design-generation process (M = 4.47) were rated Excellent, whereas customization (M = 4.39) was Very Good. Overall acceptability was Excellent (grand M = 4.42). User satisfaction received the highest criterion score (M = 4.56), followed by functionality (M = 4.48) and usability (M = 4.45). Reliability (M = 4.28) and efficiency (M = 4.30) were comparatively lower but remained Very Good. Student (M = 4.49) and faculty (M = 4.37) evaluations did not differ significantly (p = .178). Respondents primarily recommended faster loading, a broader template library, improved body-measurement modeling, and image-based styling input. The findings indicate that a human-centered AI platform can support rapid ideation and collaborative design in fashion education, although technical optimization and more granular personalization are necessary before wider institutional deployment.

Keywords: artificial intelligence; fashion design; generative design; personalization; human-computer interaction; ISO/IEC 25010; technology acceptance

INTRODUCTION

Artificial intelligence has moved from a specialized computational field into everyday creative production. Machine-learning systems can classify styles, retrieve references, forecast trends, synthesize images, and rapidly generate visual alternatives from natural-language descriptions. In fashion, these capabilities shorten the distance between an initial concept and a visible design proposal. Designers can explore silhouettes, palettes, fabrics, and stylistic combinations before committing time and materials to physical sampling. The practical attraction is obvious: digital iteration is cheaper than cutting cloth, and an algorithm does not become impatient after the twentieth variation. Nevertheless, speed alone is not evidence of educational value or design quality.

Fashion design remains a situated and human-centered activity. Fit, cultural meaning, occasion, construction feasibility, material behavior, and the client's identity cannot be reduced to visual novelty. AI-generated imagery can support ideation, but the designer must still interpret the brief, judge appropriateness, correct implausible details, and translate a visual concept into a constructible garment. Accordingly, useful AI systems should augment rather than displace human expertise. This view is consistent with human-AI collaboration, in which computational systems generate or analyze possibilities while people retain responsibility for framing, judgment, refinement, and final decisions (Daugherty & Wilson, 2018; Verganti et al., 2020).

Commercial fashion technology has advanced through recommendation systems, virtual try-on, three-dimensional visualization, automated tagging, and generative image tools. Prior work describes machine learning as a means of supporting product development, consumer personalization, and decision-making in the fashion value chain (Kim et al., 2020; Luce, 2018; Wang et al., 2021). Three-dimensional virtualization may also reduce dependence on repeated physical samples, although its usefulness depends on technical fidelity and integration with established workflows (Papachristou & Bilalis, 2022). These developments show the potential of AI, but most platforms are designed for commercial retail, large design organizations, or general-purpose image generation. Their assumptions do not always match the resources, curricula, and learning needs of state-university environments.

At Palompon Institute of Technology (PIT), as in many local educational settings, fashion-related instruction continues to depend substantially on manual sketching, conventional pattern development, and instructor-mediated feedback. These practices remain educationally important, but they can make early-stage experimentation slow. Students have limited time to generate alternatives, test combinations, and communicate a concept to instructors or prospective clients. Access to specialized commercial software and high-performance computing may also be uneven. A localized platform that combines prompting, sketch input, customization, visualization, project records, and feedback could make digital experimentation more accessible while keeping the learner and teacher inside the decision loop.

The research gap is therefore not merely whether AI can produce an attractive garment image. A more consequential question is whether an integrated, role-based platform can be accepted by intended educational users and embedded in a recognizable design workflow. Systems intended for instruction must be understandable to users with varying experience, dependable enough for repeated use, responsive on available hardware and networks, and flexible enough to represent personal design requirements. They must also support reflection and revision rather than encourage passive acceptance of the first generated output.

Conceptual foundations

The framework draws on complementary theories of intelligent systems, design, interaction, and technology adoption. Artificial Intelligence Theory provides the computational basis for transforming user inputs into generated outputs. Machine learning and generative methods identify patterns within reference data and synthesize visual responses from prompts and configured parameters (Goodfellow et al., 2016; Russell & Norvig, 2021). In the present system, AI is treated as an engine for proposal generation, not an autonomous fashion authority.

Design Thinking supplies the iterative logic of the workflow. Users define a design need, submit preferences or references, review generated concepts, communicate feedback, and refine subsequent variants. This cycle parallels ideation, prototyping, testing, and revision. Human-Computer Interaction (HCI) theory informs the clarity of navigation, visibility of system status, organization of controls, and suitability of the interface for novice and experienced users (Rogers et al., 2019; Shneiderman et al., 2024). Ergonomic considerations further require that the system fit users' cognitive and operational capabilities rather than demand unnecessary technical effort.

Technology acceptance was interpreted through the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM proposes that perceived usefulness and perceived ease of use shape acceptance (Davis, 1989), while UTAUT incorporates performance expectancy,

effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). These models are particularly relevant in education, where institutional support, digital competence, and users' prior experience can affect adoption. Software-product quality was operationalized using selected ISO/IEC 25010 characteristics, specifically functionality, reliability, usability, and performance efficiency, complemented by user satisfaction (ISO/IEC, 2011).

Objectives and hypothesis

This study aimed to develop and evaluate an AI-driven framework for personalized fashion design generation and customization for the Fashion and Apparel Technology Laboratory of PIT. Specifically, it sought to: (1) determine the functional performance of the user interface, design-generation process, and customization features; (2) describe implementation considerations associated with experience and familiarity with fashion and AI-based design tools; (3) determine acceptability in terms of functionality, reliability, usability, efficiency, and user satisfaction; (4) test whether students and faculty differed in their evaluations; and (5) identify evidence-based system enhancements. The null hypothesis stated that student and faculty evaluations would not significantly differ at $\alpha = .05$.

MATERIALS AND METHODS

Research design and setting

A descriptive-developmental research design was used. The developmental component covered requirements analysis, interface and architecture design, implementation, integration, testing, and revision of the Fashion Studio platform. The descriptive component documented users' characteristics and summarized their evaluations after hands-on interaction with the system. This design was appropriate because the inquiry addressed both the production of a working technological output and the systematic assessment of that output by intended users.

The study was conducted in the College of Technology and Engineering at Palompon Institute of Technology in Palompon, Leyte, Philippines, during School Year 2025-2026. Participants from Fashion and Apparel Technology and Information Technology contributed creative, instructional, and technical perspectives. Conducting the evaluation in the intended institutional environment allowed the researchers to observe how the framework could fit actual teaching, learning, and project-development activities.

Participants

Forty respondents participated in the evaluation: 30 students (75%) and 10 faculty members (25%). Faculty served as expert evaluators of functionality, interface design, and AI integration, while students represented the principal educational users. Twenty-two respondents (55%) were 18-25 years old, 10 (25%) were 26-35, five (12.5%) were 36-45, and three (7.5%) were 46 or older. The reported mean age was 28.30 years ($SD = 9.07$). The sample was purposively structured to obtain feedback from users who could meaningfully interact with the design and technology components of the system.

Table 1. Distribution and profile of respondents

Characteristic	Category	n	%
Role	Student	30	75.0
Role	Faculty	10	25.0
Age	18-25	22	55.0
Age	26-35	10	25.0
Age	36-45	5	12.5
Age	46 and above	3	7.5

Note. N = 40; mean age = 28.30 years, $SD = 9.07$.

System development and architecture

Development followed the System Development Life Cycle (SDLC): planning and requirements analysis, system design, framework development, implementation, testing, evaluation, and refinement (Pressman & Maxim, 2020; Sommerville, 2021). Requirements were derived from expected users, fashion-design workflows, related literature, available software and hardware, and selected ISO/IEC 25010 quality characteristics. The resulting web-based platform was designed for desktop and mobile access and provided separate designer and client roles.

The architecture comprised six coordinated modules. The input module accepted project briefs, prompts, uploaded references, sketches, garment categories, colors, fabrics, silhouettes, style tags, and other parameters. The AI-processing module interpreted these inputs and generated fashion renderings or variants. The customization module allowed users to alter selected attributes and prompts. The visualization module displayed outputs for comparison and review. The database module maintained projects, generated designs, comments, and status records. Finally, the collaboration module supported assignment, client feedback, revision requests, approval, and delivery.

Table 2. Core framework modules and functions

Module	Principal function
Input	Captures briefs, prompts, sketches, reference images, measurements, and design parameters.
AI processing	Interprets configured inputs and generates AI-assisted fashion concepts and variants.
Customization	Supports changes to silhouette, fabric, color palette, style tags, and prompts.
Visualization	Displays, compares, saves, and exports generated renderings.
Project database	Stores user roles, projects, outputs, comments, revisions, and status records.
Collaboration	Structures designer-client review, feedback, revision, approval, and delivery.

The implementation used contemporary web and AI technologies identified in the source project: HTML and CSS for presentation, JavaScript and a React-type framework for interactive components, Python and/or PHP for server-side and AI functions, MySQL for structured storage, and machine-learning libraries such as TensorFlow, PyTorch, or Scikit-learn. Cloud hosting supported remote access and AI processing. Target client hardware was an Intel Core i5-equivalent processor, at least 8 GB RAM, 256 GB solid-state storage, and a stable internet connection. Because the AI processing path was cloud dependent, network quality was expected to affect response time.

The operational workflow began with user registration and role-based authentication. A designer created a project and assigned a client; the client submitted a brief and optional references. The designer uploaded or drew a sketch, configured design parameters, entered a prompt, and requested an AI render. Generated concepts could be downloaded, stored, or regenerated as variants. The client then reviewed the concepts and either approved the project or requested revisions. The cycle continued until approval and delivery. This organization made iteration visible and preserved human control over the final design decision.

Instrument, validity, and reliability

Data were collected using a structured evaluation questionnaire adapted from ISO/IEC 25010. Functional-requirement items covered user interface, design generation, and customization. Acceptability items assessed functionality, reliability, usability, performance efficiency, and user satisfaction. The profile section recorded role, program or department, experience, familiarity with fashion-design tools, and familiarity with AI-based design systems. Open-ended questions elicited perceived strengths, encountered problems, and recommendations.

A panel with expertise in information technology, software development, educational technology, and fashion design reviewed the questionnaire for clarity, relevance, appropriateness, and alignment with the research objectives and quality criteria. Recommended revisions were incorporated before administration. A pilot test was conducted with users possessing characteristics similar to the intended respondents but excluded from the final evaluation. Internal consistency was assessed using Cronbach's alpha, with .70 specified as the minimum acceptable coefficient. The source manuscript states that this procedure established reliability; however, it does not report the obtained alpha coefficient. This omission is retained as a reporting limitation and should be corrected from the original statistical output before submission to a journal.

Items were rated on a five-point scale: 4.51-5.00, Excellent; 3.51-4.50, Very Good; 2.51-3.50, Good; 1.51-2.50, Fair; and 1.00-1.50, Poor. The source manuscript contains a minor boundary inconsistency in some sections, where 4.50 is classified as Excellent rather than Very Good. For transparency, this article applies the later stated 4.51 threshold while retaining the manuscript's reported verbal interpretations in the result tables. Journal submission should use one scale consistently and, ideally, report confidence intervals instead of relying heavily on adjectival categories.

Data collection and analysis

Permission to conduct the study was sought from the Office of the OIC-President of PIT. After approval, respondents received an explanation of the study and instructions for system testing and questionnaire completion. Student and faculty evaluations were conducted in two guided sessions. Participants interacted with the principal functions before recording their assessments. Survey responses were checked, organized, encoded, and analyzed.

Frequencies and percentages described participant characteristics and open-ended responses. Weighted means summarized functional requirements, familiarity, and software-quality criteria. Student and faculty means were compared using the inferential test reported in the source manuscript; the test yielded $p = .178$ at $\alpha = .05$. The original document does not identify the specific test statistic, degrees of freedom, assumptions, or effect size. Consequently, the present article reports only the supported conclusion and explicitly treats the missing inferential details as a limitation rather than inventing them.

Ethical considerations

Participation was described as voluntary, and collected information was used for research and system evaluation. The platform's role-based authentication and project controls were intended to limit access to authorized users. The study was situated within the requirements of the Philippine Data Privacy Act of 2012 (Republic Act No. 10173), particularly regarding responsible handling of account and project information. Before journal submission, the author should insert the formal ethics-review status or exemption, approval number if applicable, dates of consent, data-retention arrangements, and a clear statement on whether participants consented to the use of anonymized quotations.

RESULTS

Experience and technology familiarity

Most respondents were comparatively early in their design or technology experience. Twelve (30%) reported less than one year, 14 (35%) reported one to three years, eight (20%) reported four to six years, and six (15%) reported more than six years. Thus, 65% had three years or less of experience. The reported mean was 2.90 years ($SD = 2.33$). Despite this distribution, familiarity was high: fashion-design tools received a weighted mean of 4.25 and AI-based design systems 4.20, both interpreted as Very Good. Participants therefore had sufficient exposure to provide informed feedback, although onboarding remained important for less experienced users.

Table 3. Experience and familiarity indicators

Indicator	Category/statistic	n or mean	% / interpretation
Years of experience	Less than 1 year	12	30%
Years of experience	1-3 years	14	35%
Years of experience	4-6 years	8	20%
Years of experience	More than 6 years	6	15%
Familiarity	Fashion-design tools	4.25	Very Good
Familiarity	AI-based design systems	4.20	Very Good

Note. Reported mean experience = 2.90 years, SD = 2.33.

Functional requirements

The user interface received an overall mean of 4.50, based on a student mean of 4.56 and a faculty mean of 4.40. Respondents generally found the layout clear, the controls understandable, and navigation manageable. This was the highest of the three functional areas, suggesting that the basic HCI decisions successfully reduced interactional burden. The interface is particularly consequential because all downstream activities - inputting preferences, generating concepts, reviewing output, and requesting changes - depend on users being able to locate and understand system functions.

The design-generation process obtained an overall mean of 4.47 (students, 4.52; faculty, 4.42). Both groups therefore viewed the AI component favorably and considered generated possibilities useful in relation to submitted information. The result supports the system's role in rapid ideation, but it should not be interpreted as objective evidence of visual accuracy, construction feasibility, or fit. The evaluation measured user perception; no benchmark dataset or independent expert scoring of generated garments was reported.

Customization received an overall mean of 4.39 (students, 4.41; faculty, 4.32), the lowest among the three functional components. Users could modify styles, measurements, fabrics, palettes, and prompts, but the result indicates demand for more granular control. This finding is substantively important because personalization is central to the framework's claimed value. A system may produce appealing images yet still fall short if it cannot faithfully encode body measurements, garment details, fabric behavior, or client-specific constraints.

Table 4. Evaluation of functional requirements by respondent group

Functional component	Students M	Faculty M	Overall M	Interpretation
User interface	4.56	4.40	4.50	Excellent*
Design-generation process	4.52	4.42	4.47	Excellent
Customization features	4.41	4.32	4.39	Very Good

*The source manuscript reports 4.50 as Excellent, although one printed scale assigns 4.50 to Very Good. This should be standardized before submission.

Software acceptability

The framework achieved an overall acceptability mean of 4.42, reported as Excellent. User satisfaction was the highest criterion (M = 4.56), indicating a strongly positive overall experience and willingness to recommend or continue using the platform. Functionality (M = 4.48) and usability (M = 4.45) also received Excellent interpretations in the source. Respondents believed the system performed its main tasks and could be learned and navigated without excessive difficulty.

Reliability ($M = 4.28$) and efficiency ($M = 4.30$) were rated Very Good but ranked lowest. The pattern is internally coherent: a prototype can be perceived as useful and satisfying while still showing delays or occasional instability. Because AI rendering involves remote computation, file transfer, database interaction, and variable network conditions, response time may be affected by more than the interface itself. Reliability likewise includes consistent operation, error handling, stable storage and retrieval, and recovery after interruptions. These areas require technical measurement in addition to perception-based ratings.

Table 5. Acceptability of the AI-driven framework

Rank	Criterion	Weighted mean	Interpretation
1	User satisfaction	4.56	Excellent
2	Functionality	4.48	Excellent
3	Usability	4.45	Excellent
4	Efficiency	4.30	Very Good
5	Reliability	4.28	Very Good
	Grand mean	4.42	Excellent

Note. Rankings shown here cover the five stated acceptability criteria; the source manuscript also ranked functional subcomponents in a separate combined table.

Student-faculty comparison

Students provided a higher overall mean (4.49) than faculty members (4.37), but both groups evaluated the framework favorably. The source manuscript reports $p = .178$. Because this value exceeds .05, the null hypothesis was not rejected, and the study found no statistically significant difference between group evaluations. The convergence is encouraging for educational use: students, who are likely to use the platform for exploration and production, and faculty, who may supervise or assess its use, reached broadly similar judgments.

The result must nevertheless be interpreted cautiously. Only 10 faculty members were included, group sizes were unequal, and the source does not report the statistical test, assumptions, confidence interval, or effect size. Failure to reject the null hypothesis is not proof that the groups are identical. It indicates only that the available analysis did not detect a difference at the selected threshold.

Table 6. Reported comparison of student and faculty evaluations

Component	Students M	Faculty M	Source interpretation
User interface	4.56	4.40	Excellent
User experience/functionality	4.48	4.35	Excellent
Design-generation process	4.52	4.42	Excellent
Customization features	4.41	4.32	Very Good
Overall	4.49	4.37	Excellent

Note. Reported $p = .178$; $\alpha = .05$. The original manuscript does not identify the inferential test or effect size.

User comments and proposed improvements

Open-ended responses showed four recurring perceived benefits: increased creativity, faster design generation, better decision-making, and expanded design options. Respondents described the platform as a source of additional ideas and as a means of rapidly producing alternatives for client consideration. These themes support an augmentation model: the AI expands the search space, while the user evaluates and develops the preferred concept.

The most frequent specific recommendation was faster loading, mentioned by eight respondents. Six respondents indicated that no improvement was necessary, three requested additional gown templates, two requested better body-measurement modeling, and two requested image input for styling. The loading recommendation reinforces the lower efficiency score, while the latter three recommendations explain why customization trailed the other functional areas. Quantitative and qualitative results therefore point to the same priorities.

Table 7. Respondent-recommended improvements

Recommended improvement	Frequency	Development implication
Improve system loading speed	8	Optimize requests, assets, database queries, caching, and model-serving latency.
No improvement needed	6	Preserve well-received interaction patterns and avoid unnecessary complexity.
Add gown and garment templates	3	Expand the curated design library and garment categories.
Improve body-measurement modeling	2	Add validation and more precise measurement-to-design mappings.
Allow image input for styling	2	Support controlled reference-image upload and multimodal prompting.

DISCUSSION

The findings suggest that localized AI-assisted fashion design can be accepted in a state-university environment when it is embedded in a comprehensible workflow. Overall acceptability was high even though most participants had three years or less of design or technology experience. Familiarity scores indicate that respondents were not complete novices, but the strong interface and usability results still matter: perceived usefulness cannot translate into adoption if basic actions are obscure. The pattern aligns with TAM and UTAUT, which position ease, expected performance, and facilitating conditions as central to acceptance (Davis, 1989; Venkatesh et al., 2003).

The highest result, user satisfaction, should be interpreted as a promising adoption signal rather than a complete validation of the technology. Satisfaction integrates the convenience, novelty, usefulness, and affective appeal of the experience. In a creative domain, rapid visual feedback can be especially compelling. However, novelty can inflate early evaluations, and users may become more critical after extended use. A longitudinal study should therefore examine whether favorable perceptions persist after repeated assignments, more difficult briefs, and exposure to system limitations.

The design-generation score indicates that respondents considered AI outputs useful for ideation. This supports the argument that AI can broaden exploratory work by producing multiple visual alternatives faster than a purely manual workflow. Kim et al. (2020) and Wang et al. (2021) similarly describe AI as a tool for accelerating analysis and design-related decisions within fashion. Yet visual generation is only one layer of a garment-development process. Generated images may depict seams, drape, closures, layers, or proportions that are visually plausible but physically inconsistent. Future evaluation should separate aesthetic appeal, prompt fidelity, technical constructibility, material realism, fit, cultural appropriateness, and originality.

Customization was positive but comparatively weaker, exposing the difference between generic generation and genuine personalization. A prompt can request a color or silhouette, but accurate personalized design requires validated measurements, rules for ease and proportion, size and fit logic, fabric-specific behavior, and clear representations of user constraints. The suggested improvement in body-measurement modeling is therefore not cosmetic. It is a prerequisite for moving from inspirational visualization toward dependable apparel-development support. Integration with pattern-making or three-dimensional garment simulation could eventually close this gap, but such expansion would require new validation, computing resources, and domain expertise.

Reliability and efficiency were the weakest quality areas. This result is unsurprising for a cloud-dependent prototype, but it is also the part most likely to determine whether the system survives beyond a demonstration. Slow generation interrupts creative flow; failed requests reduce trust; and inconsistent data storage can undermine project collaboration. Performance should be instrumented using median and percentile response times, request failure rate, model queue time, upload duration, database latency, and recovery behavior. Reliability testing should include repeated sessions, network interruptions, concurrent users, invalid inputs, large files, and browser or mobile-device variation.

The similarity between student and faculty evaluations is institutionally useful because adoption usually fails when a tool serves only one side of the classroom. Students may value speed and creative options, whereas faculty may emphasize pedagogy, accountability, and quality. Their broadly convergent evaluations suggest that Fashion Studio can function as a shared instructional environment. Nevertheless, the nonsignificant result should not be overstated because the sample was small and unequal. Replication with larger groups, multiple institutions, and stratification by discipline or experience would provide a stronger basis for generalization.

The framework also raises ethical and pedagogical concerns that were not fully tested in the source study. Generated outputs may reflect biases in training data, reproduce stereotyped bodies or styles, or resemble copyrighted works. Reference-image upload creates privacy and intellectual-property risks. Students may confuse rapid generation with mastery unless assignments require documentation of prompts, design rationale, revisions, source acknowledgment, and critical reflection. Institutional deployment should therefore include acceptable-use rules, disclosure of AI assistance, privacy controls, content moderation, authorship guidance, and procedures for contesting inappropriate outputs (Ahmad & Khan, 2025).

Practical implications for fashion education

Fashion Studio can be positioned as a pre-production ideation and communication tool. Instructors can use it to compare how changes in brief, silhouette, palette, or material reference alter an output; students can critique AI proposals and explain why a generated concept would or would not be constructible. Client and designer roles can support simulated professional projects in which requirements, feedback, revisions, and approval are documented. This approach preserves foundational manual and technical skills while allowing students to engage critically with emerging technology.

A phased institutional implementation is advisable. The first phase should stabilize loading, error handling, authentication, storage, and browser compatibility. The second should expand curated templates and introduce validated measurement input. The third can explore multimodal reference images, trend data, or three-dimensional visualization. Each phase should include usability testing, technical performance benchmarks, and pedagogical review. Adding features faster than they can be validated would merely produce a larger prototype, not a better educational system.

Proposed enhancement priorities

Table 8. Evidence-based enhancement roadmap

Priority	Action	Evaluation metric	Time horizon
1	Optimize loading, model requests, database queries, and error recovery.	Median/P95 response time; failure rate; successful recovery rate.	Short term
2	Expand curated garment and gown templates.	Template coverage; selection/use rate; expert relevance rating.	Short-medium term
3	Strengthen measurement capture and body-model validation.	Input validity; fit/proportion error; expert agreement.	Medium term
4	Add controlled image-based styling references.	Upload success; prompt/reference fidelity; privacy compliance.	Medium-long term
5	Develop user orientation and AI-literacy activities.	Task completion; critical-evaluation rubric; adoption over time.	Continuous

Limitations and Future Research

Several limitations constrain the claims that can be made. First, the evaluation involved only 40 respondents from one institution, including 10 faculty members, limiting statistical power and generalizability. Second, outcomes were based largely on self-reported perceptions following system interaction. No objective comparison was made against manual design, commercial software, or another AI tool. Third, the manuscript does not report the obtained Cronbach's alpha, item-level statistics, missing-data treatment, inferential test statistic, degrees of freedom, confidence intervals, or effect size. Fourth, the evaluation did not provide objective measures of generation latency, uptime, failure rate, prompt fidelity, garment constructibility, fit accuracy, accessibility, security, or learning achievement. Fifth, short-term acceptance may reflect novelty and does not establish sustained use.

Future research should employ a larger, multi-institutional sample and a transparent statistical analysis plan. Experimental or quasi-experimental designs could compare design time, number and diversity of concepts, rubric-based quality, technical feasibility, and learner outcomes across manual, conventional digital, and AI-assisted workflows. Repeated-measures evaluation could determine whether learning and satisfaction persist. Domain experts should independently assess construction feasibility, fit, material plausibility, and originality. Technical studies should benchmark response time and reliability under varying hardware, network, and concurrent-load conditions. Research should also examine bias, authorship, privacy, intellectual property, accessibility, and the effects of AI assistance on students' independent design skills.

CONCLUSION

The study developed and evaluated Fashion Studio, an AI-driven, role-based framework for personalized fashion-design generation and customization. Among 30 students and 10 faculty members, the platform achieved an overall mean of 4.42 and was reported as highly acceptable. User satisfaction, functionality, usability, interface design, and generation received the strongest evaluations. Reliability, efficiency, and customization remained favorable but emerged as the principal improvement areas. Student and faculty evaluations did not significantly differ ($p = .178$), although the small and unequal groups require cautious interpretation.

The evidence supports the platform's use as an assistive environment for ideation, visualization, and designer-client collaboration in fashion education. It does not yet establish objective design accuracy, fit, construction feasibility, learning impact, or readiness for unrestricted institutional scale. The next development cycle should prioritize measured performance optimization, robust error handling, broader templates, validated body-measurement modeling, responsible image input, and explicit governance for AI-assisted creative work. The designer must remain the editor, critic, and accountable decision-maker; the machine is fast, but it still cannot sew its way out of a bad assumption.

Declarations

Ethics approval and consent to participate. Institutional approval was obtained to conduct the evaluation at Palompon Institute of Technology, and participation was voluntary. The author should insert the formal ethics-review determination, approval or exemption number, and consent procedure before submission.

Consent for publication. No directly identifying participant information is reported. Confirmation regarding consent for anonymized quotations should be added before submission.

Data availability. The dataset supporting the reported means is not appended to the source manuscript. A repository link or a justified data-availability restriction should be supplied by the author.

Conflict of interest. The author should confirm whether any financial or non-financial conflicts exist.

Funding. The author should insert the funding source and grant number, or state that the research received no external funding.

Author contributions. Madilyn A. Marquez: conceptualization, system requirements, investigation, data curation, analysis, writing, and project administration. This statement should be checked against actual contributions before submission.

REFERENCES

1. Ahmad, S., & Khan, M. (2025). Ethics of artificial intelligence in creative industries: A handbook for the digital age. Routledge.
2. Daugherty, P. R., & Wilson, H. J. (2018). Human + machine: Reimagining work in the age of AI. Harvard Business Review Press.
3. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. <https://doi.org/10.2307/249008>
4. DeVellis, R. F. (2017). Scale development: Theory and applications (4th ed.). SAGE Publications.
5. Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.
6. International Organization for Standardization. (2011). ISO/IEC 25010:2011 systems and software engineering - Systems and software quality requirements and evaluation (SQuaRE) - System and software quality models.
7. Kendall, K. E., & Kendall, J. E. (2020). Systems analysis and design (10th ed.). Pearson.
8. Kim, H., Lee, S., & Park, J. (2020). Artificial intelligence in fashion design: A review of machine learning applications in clothing design. *Fashion and Textiles*, 7(1), 1-15. <https://doi.org/10.1186/s40691-020-00218-2>
9. Lazar, J., Feng, J. H., & Hochheiser, H. (2024). Research methods in human-computer interaction (3rd ed.). Morgan Kaufmann.
10. Luce, L. (2018). Artificial intelligence for fashion: How AI is revolutionizing the fashion industry. Apress. <https://doi.org/10.1007/978-1-4842-3937-9>
11. Nielsen, J. (1994). Usability engineering. Morgan Kaufmann.
12. Papachristou, E., & Bilalis, N. (2022). Can 3D virtualization eliminate physical sampling? An industry-focused survey. *Journal of Fashion Marketing and Management*, 26(1), 114-130. <https://doi.org/10.1108/JFMM-03-2021-0071>
13. Pressman, R. S., & Maxim, B. R. (2020). Software engineering: A practitioner's approach (9th ed.). McGraw-Hill Education.
14. Rogers, Y., Sharp, H., & Preece, J. (2019). Interaction design: Beyond human-computer interaction (5th ed.). Wiley.
15. Russell, S., & Norvig, P. (2021). Artificial intelligence: A modern approach (4th ed.). Pearson.
16. Schwab, K. (2017). The fourth industrial revolution. Crown Business.
17. Shneiderman, B., Plaisant, C., Cohen, M., Jacobs, S., Elmqvist, N., & Diakopoulos, N. (2024). Designing the user interface: Strategies for effective human-computer interaction (7th ed.). Pearson.
18. Sommerville, I. (2021). Engineering software products: An introduction to modern software engineering. Pearson.
19. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425-478. <https://doi.org/10.2307/30036540>
20. Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, 36(1), 157-178.
21. Verganti, R., Vendraminelli, L., & Iansiti, M. (2020). Design in the age of artificial intelligence. *Harvard Business Review*, 98(2), 66-75.
22. Wang, Y., Zhang, Y., & Chen, X. (2021). Artificial intelligence in fashion industry: Applications, challenges, and future trends. *IEEE Access*, 9, 132124-132137. <https://doi.org/10.1109/ACCESS.2021.3114635>