# SketchAI: A "Sketch-First" Approach to Incorporating Generative AI into Fashion Design


Richard Lee Davis*
KTH Royal Institute of Technology
Stockholm, Sweden
rldavis@kth.se

Kevin Fred Mwaita*
Free University of Bozen-Bolzano
Bolzano, Italy
kmwaita@unibz.it

Livia Müller
HAIS
Bern University of Applied Sciences
Bern, Switzerland
livia.mueller@bfh.ch

Daniel C. Tozadore
CHILI
EPFL
Lausanne, Switzerland
daniel.tozadore@epfl.ch

Aleksandra Novikova
CHILI
EPFL
Lausanne, Switzerland
aleksandra.novikova@epfl.ch

Tanja Käser
EFPL
Lausanne, Switzerland
tanja.kaeser@epfl.ch

Thiemo Wambsganss
HAIS
Bern University of Applied Sciences
Bern, Switzerland
thiemo.wambsganss@bfh.ch


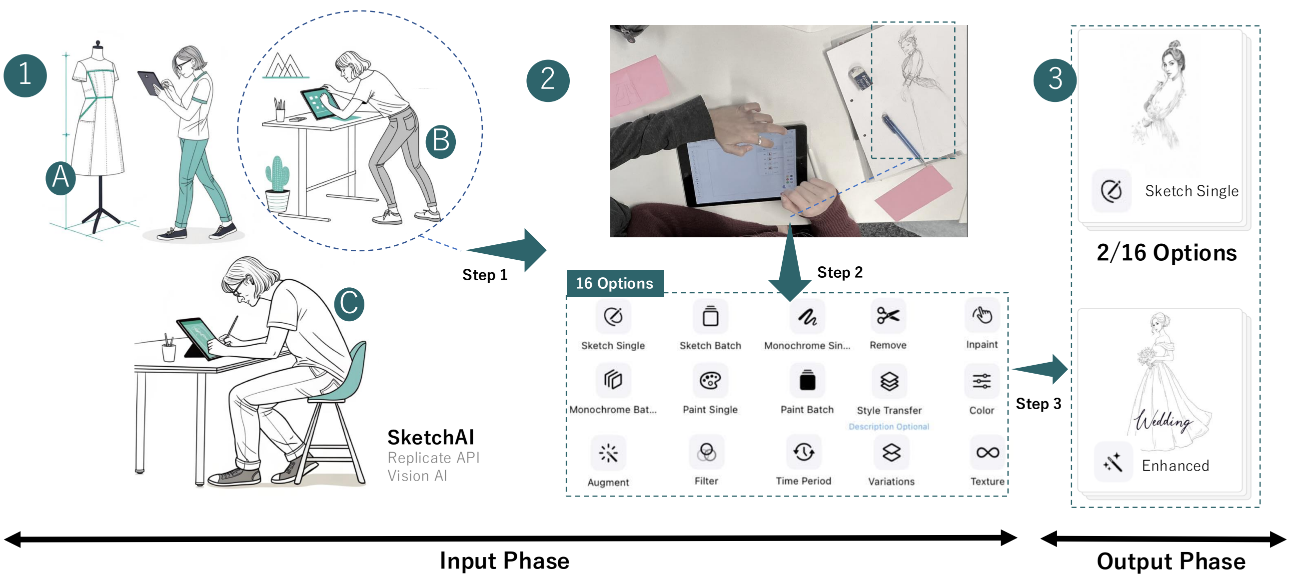


**Figure 1: We introduce SketchAI, a tool for transforming hand-drawn sketches into improved designs. Step 1 (Upload) lets users capture a photo (1A), upload an existing image (1B), or create a new sketch (1C). In Step 2 (Enhancement), SketchAI processes the input using one of 16 options, such as Sketch Single or Enhanced, applying features such as Sketch Single or Enhanced to generate improved versions (2). Step 3 (Results and Iterations) allows users to select one enhanced result (e.g., 2/16 options) for refinement (3), enabling further adjustments.**

*Both authors contributed equally to this research.


*CHI EA '25, Yokohama, Japan*


## Abstract

Generative AI technologies are increasingly being incorporated into creativity support tools. However, most generative AI tools rely on



ACM ISBN 979-8-4007-1395-8/25/04
https://doi.org/10.1145/3706599.3719782

text-based prompting, requiring users to translate visual ideas into linguistic descriptions. This approach is misaligned with the sketch-driven workflows of creative professionals. To address this gap, we introduce SKETCHAI, a novel sketch-first interface for diffusion models that allows practitioners to use real-time sketching on a tablet computer to guide model outputs. Through a qualitative study with 29 fashion design apprentices, we explored the interface's potential impacts on creative workflows. While some participants identified use cases where SKETCHAI streamlined routine tasks, others expressed concerns about its potential to undermine creative agency and exploration. These findings unearthed hidden complexity: while generative AI can support some aspects of creativity, its core capabilities may challenge the central identity of creative practitioners. While SKETCHAI does not resolve this problem, it does take a meaningful step towards reconciliation.

## CCS Concepts

**• Computing methodologies → Artificial intelligence**; **• Human-centered computing → Graphical user interfaces**; **Interactive systems and tools**.

## Keywords

Creativity Support Tools, CSTs, Generative AI, Artificial Intelligence, Sketch-Based Input, Diffusion Models

**ACM Reference Format:**
Richard Lee Davis, Kevin Fred Mwaita, Livia Müller, Daniel C. Tozadore, Aleksandra Novikova, Tanja Käser, and Thiemo Wambsganss. 2025. SketchAI: A "Sketch-First" Approach to Incorporating Generative AI into Fashion Design. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems (CHI EA '25), April 26–May 01, 2025, Yokohama, Japan.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3706599.3719782

## 1 Introduction and Related Work

Creativity support tools (CSTs) are increasingly incorporating generative AI (genAI) technologies like diffusion models [12, 18] and generative adversarial networks [11, 14] to enhance creative processes. These tools aim to amplify human creativity by supporting divergent and convergent ideation and facilitating creative workflows. Among this class of CSTs, many rely on text-based prompting interfaces to steer the output of generated content [1, 3, 4, 9, 19]. While these interfaces have been shown to be effective and accessible for general audiences, they require users to translate visual ideas into linguistic descriptions, which may not align with visual creative workflows [7, 17].

Visual creative professionals, such as fashion designers, have workflows that are centered around sketching and image curation. For example, fashion designers typically iterate on silhouettes, color palettes, and styling elements through rough sketches, often supplemented by mood boards and physical prototypes, before finalizing concepts [16]. Translating these visual-first workflows into text-based prompts can be cumbersome, prompting the broader question of how genAI tools might evolve to better align with established professional practices.

An emerging class of genAI CSTs leverage unique capabilites of AI architectures like generative adversarial networks (GANs) [11, 14] or technical extensions to diffusion models like ControlNet [22] to incorporate more visual modes of interaction that better allow for multimodal interactivity. GAN-based tools such as StyleMe [21] and Fashion-Sketcher [10] support designers in creating and refining sketches based on input images, leveraging style transfer abilities of GANs. Generative.fashion is another GAN-based tool that enables the generation of designs and exploration of variations through graphical interfaces, utilizing the GAN's semantically meaningful latent space [6, 7]. While these tools demonstrate the potential of GANs to facilitate visual workflows, their technical limitations—such as a restricted range of outputs and challenges in achieving high-fidelity details—may constrain their applicability in professional fashion design settings.

In contrast to GANs, pre-trained diffusion models are capable of generating high-quality images from a wide variety of domains and styles, and recent technological advancements in sketch- and stroke-guided image generation with diffusion models are creating new possibilities for multimodal control of their outputs [5, 20, 22]. Building on these innovations, an emerging direction in HCI research seeks to bring genAI tools into closer alignment with visual workflows by using sketches and visual annotations to help control the image generation process [2, 8, 13]. However, few tools have adopted a "sketch-first" methodology, where sketching serves as the principal driver throughout the creative process of ideation, image generation, editing, and refinement.

In this paper, we introduce SKETCHAI, a novel sketch-first interface for image-generating diffusion models. We hypothesize that by preserving the sketch-based processes of practitioners, a sketch-first approach can provide better support for the integration of genAI into creative workflows. We evaluate its potential impacts through a qualitative study with $N = 29$ apprentices who used SKETCHAI in two authentic role-play activities. Through semi-structured focus-group interviews and observational analyses we aimed to answer the following research questions:

- RQ1: How do creative practitioners perceive and evaluate a sketch-first AI interface?
- RQ2: What aspects of the sketch-driven workflow contribute to or relieve tensions around integrating genAI into the creative process?
- RQ3: How might future genAI creativity support tools be designed to better align with and support professional practices in visually oriented creative disciplines?

Contrary to our initial hypothesis—that a sketch-first system would be perceived as more supportive and better aligned with sketch-based workflows—participant feedback revealed mixed perspectives. While apprentices did point out specific use cases where SKETCHAI could streamline routine tasks, they also expressed concerns about its potential to take over the creative and exploratory aspects of their work. Broad concerns about the potentially harmful impacts of genAI partially overshadowed discussions of the specific benefits a sketch-first interface might offer. We offer three key contributions:

- A novel sketch-first interface (SKETCHAI) that enables practitioners to guide diffusion-based image generation through real-time drawing.
- A qualitative study of SKETCHAI's use among fashion design apprentices, revealing mixed perspectives on the tool and its utility.

- An analysis of how these perspectives reflect broader concerns about genAI's effects on eroding creative autonomy and the meaningfulness of their work.

## 2 SketchAI Prototype

SketchAI lets users create digital art on tablets using both manual drawing and AI generation. The interface uses layers and combines drawing tools with image processing features. Built with SwiftUI, this section covers the system's features and architecture.

### 2.1 System Features

The user interface (UI) integrates six functional areas (as seen in Figure 2). On the left-hand side, the primary drawing toolbar *(F1)* provides essential editing capabilities including selection, drawing, cropping, rotation, and text tools. The right side hosts the layer management panel *(F2)*, implementing a stack-based system where new layers are automatically positioned at the top of the hierarchy, ensuring non-destructive editing by preserving original work in lower layers and maintaining clear visibility control through toggleable layer display.

Adjacent to the layer manager, the AI tools panel *(F3)* organizes its capabilities into four categories. The Quick Actions category houses seven tools and also provides transformations in both Single (1 variation) and Batch (4 variations): Sketch Single/Batch converts images to pencil drawings by processing the original image through line and shading analysis, Monochrome Single/Batch transforms images into black and white versions by analyzing tonal values, Paint Single/Batch converts images into painted styles by simulating brush strokes and artistic techniques, and the Enhance mode improves image quality through AI upscaling and detail refinement. The Edit category offers six tools: Style Transfer, which applies artistic styles from one image to another, Filter, which processes images through predefined visual effects, Time Period, which adapts images to specific historical time period aesthetics, Color, which provides precise control over color attributes and relationships, Texture, which modifies surface qualities through pattern and material simulation, and Augment, which analyzes the image to integrate new AI-generated elements. The Generate category offers two tools: Remove, which uses the Bria API to analyze and separate foreground from background for clean background elimination, and Inpaint, which allows designers to draw masks over areas they want to modify and generate new content based on provided prompts. The Style category features the Variation tool, which creates alternative versions of the image while maintaining its core characteristics.

At the bottom, the pencil toolkit *(F4)* implements pressure-sensitive brush dynamics with customizable thickness, opacity, and color selection. The main canvas *(F5)* serves as the central workspace, providing real-time visualization of both manual edits and AI processing results, while the control panel *(F6)* at the top manages file operations and canvas settings, including resolution adjustments, zoom controls, and opacity settings for fine-tuned visual refinement.

## 3 System Architecture

The system uses three data flows as seen in Figure 5 in the Appendix: 1. Image Creation (Real-time Drawing & Processing), 2. Image Enhancement (Smart Background Processing), and 3. AI Assistance (Intelligent Enhancement). A SwiftUI frontend handles user interaction through canvas and controls like stylus input *(A)*, while a Layer System manages state and history *(B)*. The ChatGPTManager *(C)* uses GPT-4 to refine user prompts, send notifications, and handle errors during prompt processing. The system connects to three external services: Replicate Services for image processing *(D)*, OpenAI for vision-text analysis *(E)*, and Bria for background removal *(F)*. These services were selected for their specific strengths: Replicate's processing capabilities, OpenAI's vision understanding, and Bria's segmentation precision.

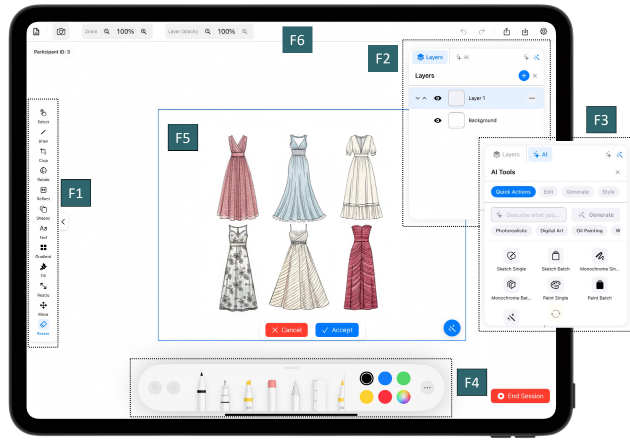


**Figure 2: Prototype interface illustrating the layer-based drawing system with AI-assisted features.**

*3.0.1 Image Creation (Flow 1).* Image Creation focuses on real-time drawing and editing on the canvas using the basic editing tools. The Layer System processes these inputs locally to provide immediate feedback. AI models enhance these base designs by applying additional image processing. For this reason, a variety of models are used within the Replicate Services API.

*3.0.2 Image Enhancement (Flow 2).* This flow introduces background processing capabilities. When background removal is initiated by a user, the system first converts images to PNG format with unique identifiers. After sending these to Bria's servers, the system receives processed images with quality metadata, which it uses to verify the output before creating new layers with the processed content.

*3.0.3 AI Assistance (Flow 3).* AI Assistance combines GPT-4's vision and language processing to elevate the design experience. Tools such as Enhance, Variation, and Time Period use vision to interpret the canvas image and generate descriptive details to guide transformations. Prompt enhancement refines user inputs to improve outputs, for example, when a designer wants to transform an image with a simple prompt such as "make it more vintage," the system refines the prompt to something more specific, such as "adapt the garment's silhouette and details to reflect 1950s haute couture characteristics." The system uses a guidance scale of 7.0 to 8.5 to maintain artistic consistency and is ideal for style transfer, ensuring the final look stays true to the original style. For texture and color adjustments, a guidance scale of 7.0 to 7.5 ensures stable, high-quality modifications.

Error-handling mechanisms are integrated across the system to maintain responsiveness. When processing fails, inference steps are reduced (e.g., from 50 to 30) to ensure functionality. Polling intervals (e.g., 2 seconds for background removal and 3 seconds for style transfer) optimize server load without delaying interactions.

Figure 3 displays the four models we use in the app, along with their performance analysis and tool mapping, to assist designers in evolving their ideas and visualizing their final digital concepts. Each model serves specific functions based on tested capabilities. Flux-Canny-Pro uses 50 inference steps because detailed edge detection, particularly important for fashion design elements like seam lines and fabric patterns, requires this higher iteration count to maintain a much higher fidelity. Flux-Depth-Pro was optimized to 30 processing steps, which provides the best balance for depth-based texture modifications. At this level, the algorithm achieves peak image quality: higher steps yield diminishing returns, while fewer steps degrade image integrity. Flux-1.1-Pro uses a 25-step process as the minimum viable threshold, prioritizing a trade-off between processing speed and structural preservation.

Figure 3A we measure the success rates, processing times, output quality, and completion status and use what we find to tweak the models for improvement. These metrics determined model selection and the use cases which informed the toolkits to build in each category.

Figure 3B maps the sixteen tool-model relationships. Recraft-v3 handles Period for time period matching, Filter for color grading, and Variations for alternative versions. Flux-1.1 processes Paint Single and Batch for style conversion and Transfer for style movement between images. Flux-Canny executes four tools: Sketch Single and Batch for pencil drawings, Monochrome Single and Monochrome Batch for black/white conversion. Flux-Depth manages Color for attributes, Texture for patterns, Enhance for quality, and Augment for image modifications. The Replicate API handles Inpaint for content filling, while Bria-API executes Remove for background separation.

The Layer System preserves editing history in a composition stack, creating new layers for each operation. We also use identifiers and metadata to track data flow between components and log each user interaction in a spreadsheet.

## 4 User Study with Fashion Design Apprentices

A workshop-based methodology was employed to evaluate the SketchAI prototype (see Figure 3). A total of $n = 29$ apprentices from two classes of a vocational design apprenticeship participated. They varied in their level of training but shared a common focus on design.

### 4.1 Procedure

Apprentices were first introduced to the workshop's aims and completed a brief set of qualitative pre-study questions. These questions collected demographic data, probed participants' familiarity with AI technology, and explored their initial openness to integrating AI in their design practice. The SketchAI prototype was then demonstrated, illustrating its core features and potential applications.

Following this introduction, participants worked through scenario-based tasks derived from typical design apprenticeship requirements. First, they freely explored the prototype to become familiar with its interface and features. Next, they enacted a client communication scenario in which they attempted to design an elegant, summery dress based on specific requirements. This was followed by a second scenario, focused on inspiration and idea generation for the same dress, but with considerably less-defined requirements. These tasks allowed participants (as seen in Figure 4) to engage with the prototype in both structured and exploratory ways.

Upon completing these scenario-based tasks, participants were invited to reflect on their experiences by giving feedback on both the prototype itself and the broader role of AI in design. Specifically, they were instructed to identify features they found most or least appealing in the prototype, along with the reasons for their preferences. They also considered whether—and under what circumstances—they might integrate AI into future design processes, as well as how their perceptions of AI may have shifted through hands-on use of the prototype. Finally, participants reflected on AI's influence on creativity, discussing whether they regarded AI as a facilitator of innovative thinking or a potential obstacle to the design process.

### 4.2 Data Collection

To capture these insights, the study employed a two-stage data collection approach. First, apprentices individually reflected on their experiences by documenting their personal thoughts in writing, enabling the recording of initial, unfiltered impressions. Following this, a moderated group discussion was held to encourage shared reflections and debate. This collective format allowed participants to build on each other's viewpoints, thereby generating a richer understanding of how AI might be integrated into, or affect, design practice.

### 4.3 Data Analysis

All collected data were qualitative. A deductive analysis was undertaken, focusing on (i) perceptions of the AI prototype (positive and negative experiences), (ii) intention to use SketchAI or similar tools in future practice, and (iii) the perceived role of AI in supporting creativity within the design domain. These themes provided insights to understand apprentices' views on AI's place in their evolving professional practice. The results are presented according to these point of focus next subsection.

As for the software used in the analysis, LLMs were employed for different purposes. The image classification of participants' notes on the post-its was done using GPT-4, the transcription and translation of the group interview audio using noScribe[1], and for insights and frequency counting of topics in the transcripts (o1 and GPT-4[2]). All of these steps were later validated by the researchers. The original writing, prompts, and scripts were kept and can be accessed for evaluation at request.

[1]https://github.com/kaixxx/noScribe
[2]https://platform.openai.com/docs/models

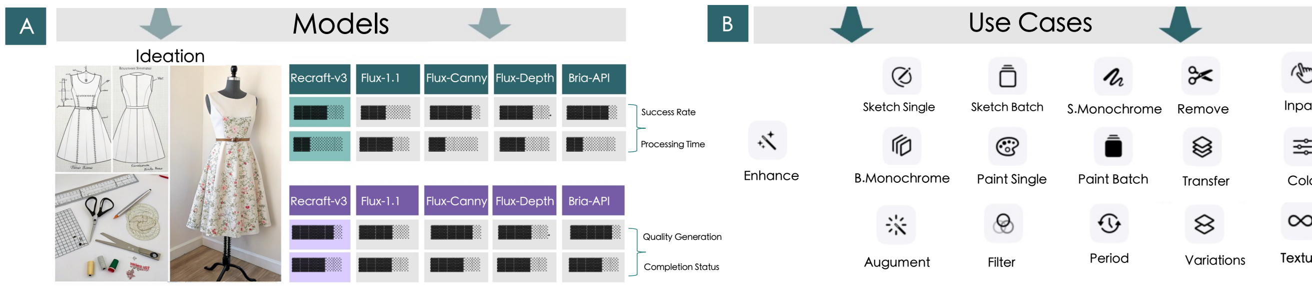


**Figure 3: Performance metrics include success rate, speed, quality, and completion status(A) and use cases(B). Each task uses specific models: For example, Recraft-v3 for Time Period, Filter and Variations; Flux-1.1 for Paint and Transfer; Flux-Canny for Sketch; Flux-Depth for Color, Texture, Enhance and Augment. Background removal uses Bria-API.**

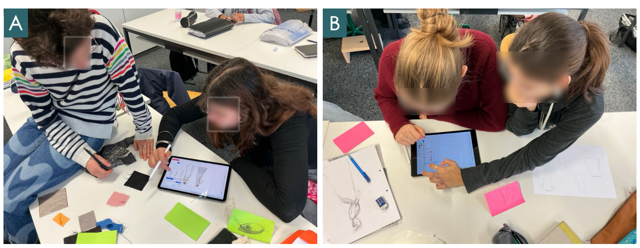


**Figure 4: Design Apprentice groups (A) and (B) using SketchAI to complete a task.**

## 4.4 Results

*4.4.1 (i) Perceptions of the AI prototype.* When asked about what they liked about the prototype they experienced, the following positive aspects of the prototype were mentioned: its versatility and multiple options (n=8), quick image generation (n=5), and the ability to produce realistic and high-quality results (n=5). Participants appreciated its support for various art styles and customization features (n=5), along with its capacity to foster creativity and provide inspiration (n=4), for instance "Super cool, great support for visualization". The tool was also noted for its ease of use and intuitive interface (n=4), making it accessible for different users, because "The app is self-explanatory and not complicated." Additionally, its utility in specific use cases, such as generating technical drawings, invitations, or design ideas (n=3), was positively mentioned.

When prompted about things they did not like, frequently mentioned topics were: accuracy problems (n=12), "Fails to generate what I want."; usability concerns (n=10), e.g. "Eraser didn't really work," performance issues (n=9), "It takes some time for results to be displayed". Concerning the experience as a whole, creative limitations were mentioned (n=7), expressed by the sentences "Cannot achieve photorealism," "Fails with detailed or individual designs," "Doesn't handle creative input effectively."

*4.4.2 (ii) Intention to use SketchAI or similar tools in future practice.* When asked whether they would adopt SketchAI or similar tools in their workflow, the apprentices' reponses were mixed. Positive feedback was slightly more prevalent, with participants highlighting advantages such as Sketch AI's usefulness for visualization, brainstorming, and inspiration (n=10), as well as its support for technical drawings (n=6), customer meetings and presentations (n=5), and learning or concept clarification (n=4). However, negative views were also significant, with frequent concerns about AI's inability to handle precise or detailed tasks effectively (n=6), its limitations in creative or manual design processes (n=5), and its inefficiency in professional workflows like customer meetings (n=4).

Skepticism about AI's impact on individuality and creativity (n=4) and a preference for personal skills over AI reliance (n=3) were also common. Privacy concerns (n=1) and recognition of its inability to replace hands-on skills (n=3) further emphasized doubts. While some acknowledged its potential for experimentation (n=2), overall opinions were divided, with practical benefits often counterbalanced by concerns over precision, creativity, and usability in professional settings.

*4.4.3 (iii) AI in supporting creativity within the design domain.* Finally, participants provided their overall perception about the usage of genAI in their professional domain, primed by their experience with our tool. Their opinions were again divided, where positive (n=13) and negative answers were observed. Positive answers included statements such as "I find it very nice and helpful," "Very practical, especially at work," "I think we need more time working with AI to understand it better," and "Nice to have, if needed," which express appreciation or utility of AI for learning, work, and inspiration. On the other hand, some participants expressed negative answers with intense affirmations, like "Catastrophic. People should think for themselves," "I think AI is not really needed in the fashion world," and "I think it should NEVER be used in the design process," all expressing concerns about over-reliance or inappropriateness of AI in certain fields. Only 2 participants reported realizing a change in their initial opinion after being exposed to the proposed tool. Their statements were "I was a bit skeptical, but I think the AI tool is very good," and "It hasn't changed much, but I've seen once again what it can be good for."

# 5 Discussion

The introduction of SketchAI—a sketch-first, genAI creativity support tool—helps address a need to align AI technologies with the visually driven workflows of creative professionals. Through a qualitative study with $N = 29$ fashion design apprentices, we found that SketchAI was appreciated for its ability to streamline routine tasks, enhance ideation processes, and provide fast, high-quality visual outputs. However, the study also surfaced critical challenges and reservations that underscore the complexity of integrating AI into professional creative practices. The apprentices raised concerns about the tool's potential to erode creative autonomy and individuality, diminishing the meaningful aspects of their work. Many expressed apprehension that use of AI tools might lead to impersonal or "soulless" outputs, and shared broader concerns around ethical implications and privacy concerns.

These findings, although controversial, are aligned with the literature. According to Kelly *et al.* [15], studies investigating AI acceptance should consider that willingness and rejection can happen together, rather than treating them as opposites. Overall, these outcomes illustrate the variety of designers' attitudes toward AI: from a guarded interest in incorporating it as an auxiliary tool to a deeply entrenched resistance based on philosophical and practical objections. Nonetheless, it was possible to observe small shifts in their perceptions about AI tools, and even participants with strong opinions against the use of AI claimed they enjoyed using the app.

The opinions about genAI revealed a situation that was more complex than we previously realized. Aligning genAI with visual workflows alone may not be sufficient to support creative work. To some creative practitioners, genAI tools pose a fundamental threat to their identity. However, the aversion we observed might also be a "novelty effect" that diminishes over time as practitioners discover ways to leverage genAI technologies without compromising the meaningful and creative aspects of their work. These dual possibilities warrant further investigation and motivate further engagement with creative professionals to navigate this complexity.

## Acknowledgments

Thanks to the instructors and apprentices who took part in our studies.

## References


[1] Shm Garanganao Almeda, J.D. Zamfirescu-Pereira, Kyu Won Kim, Pradeep Mani Rathnam, and Bjoern Hartmann. 2024. Prompting for Discovery: Flexible Sense-Making for AI Art-Making with Dreamsheets. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery, New York, NY, USA, 1–17. doi:10.1145/3613904.3642858

[2] Daniel D. Braghis and Haiming Liu. 2024. Conversational Image Search: A Sketch-based Approach. In *Proceedings of the 2024 International Conference on Multimedia Retrieval (ICMR '24)*. Association for Computing Machinery, New York, NY, USA, 1265–1269. doi:10.1145/3652583.3657594

[3] Qianqian Chen, Tianyi Zhang, Maowen Nie, Zheng Wang, Shihao Xu, Wei Shi, and Zhao Cao. 2023. Fashion-GPT: Integrating LLMs with Fashion Retrieval System. In *Proceedings of the 1st Workshop on Large Generative Models Meet Multimodal Applications*. ACM, Ottawa ON Canada, 69–78. doi:10.1145/3607827.3616844

[4] Xiaoyu Chen, Zirui Ma, Xinhao Jiang, Yingzhao Jian, Xuelin Yao, and Peiping Wu. 2024. Lumos: AI-driven prompt optimisation tool for assisting conceptual design. *Journal of Engineering Design* 35, 12 (Dec. 2024), 1597–1623. doi:10.1080/09544828.2024.2396195 Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/09544828.2024.2396195.

[5] Shin-I. Cheng, Yu-Jie Chen, Wei-Chen Chiu, Hung-Yu Tseng, and Hsin-Ying Lee. 2023. Adaptively-Realistic Image Generation From Stroke and Sketch With Diffusion Model. 4054–4062. https://openaccess.thecvf.com/content/WACV2023/html/Cheng_Adaptively-Realistic_Image_Generation_From_Stroke_and_Sketch_With_Diffusion_Model_WACV_2023_paper.html

[6] Richard Lee Davis, Thiemo Wambsganss, Wei Jiang, Kevin Gonyop Kim, Tanja Käser, and Pierre Dillenbourg. 2023. Fashioning the Future: Unlocking the Creative Potential of Deep Generative Models for Design Space Exploration. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems (CHI EA '23)*. Association for Computing Machinery, New York, NY, USA, 1–9. doi:10.1145/3544549.3585644

[7] Richard Lee Davis, Thiemo Wambsganss, Wei Jiang, Kevin Gonyop Kim, Tanja Käser, and Pierre Dillenbourg. 2024. Fashioning Creative Expertise with Generative AI: Graphical Interfaces for Design Space Exploration Better Support Ideation Than Text Prompts. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems (CHI '24)*. Association for Computing Machinery, New York, NY, USA, 1–26. doi:10.1145/3613904.3642908

[8] Hanhui Deng, Jianan Jiang, Zhiwang Yu, Jinhui Ouyang, and Di Wu. 2024. CrossGAI: A Cross-Device Generative AI Framework for Collaborative Fashion Design. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 8, 1 (March 2024), 1–27. doi:10.1145/3643542

[9] Yujuan Ding, Yunshan Ma, Wenqi Fan, Yige Yao, Tat-Seng Chua, and Qing Li. 2024. FashionReGen: LLM-Empowered Fashion Report Generation. In *Companion Proceedings of the ACM Web Conference 2024 (WWW '24)*. Association for Computing Machinery, New York, NY, USA, 991–994. doi:10.1145/3589335.3651232

[10] Junkai Fang, Xiaoling Gu, and Min Tan. 2020. Fashion-Sketcher: A Model for Producing Fashion Sketches of Multiple Categories. In *Pattern Recognition and Computer Vision*, Yuxin Peng, Qingshan Liu, Huchuan Lu, Zhenan Sun, Chenglin Liu, Xilin Chen, Hongbin Zha, and Jian Yang (Eds.). Springer International Publishing, Cham, 544–556. doi:10.1007/978-3-030-60639-8_45

[11] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. 2014. Generative Adversarial Nets. In *Advances in Neural Information Processing Systems*, Vol. 27. Curran Associates, Inc. https://proceedings.neurips.cc/paper_files/paper/2014/hash/5ca3e9b122f61f8f06494c97b1afccf3-Abstract.html

[12] Jonathan Ho, Ajay Jain, and Pieter Abbeel. 2020. Denoising Diffusion Probabilistic Models. In *Advances in Neural Information Processing Systems*, Vol. 33. Curran Associates, Inc., 6840–6851. https://proceedings.neurips.cc/paper/2020/hash/4c5bcfec8584af0d967f1ab10179ca4b-Abstract.html

[13] Jianan Jiang, Di Wu, Hanhui Deng, Yidan Long, Wenyi Tang, Xiang Li, Can Liu, Zhanpeng Jin, Wenlei Zhang, and Tangquan Qi. 2024. HAIGEN: Towards Human-AI Collaboration for Facilitating Creativity and Style Generation in Fashion Design. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 8, 3 (Aug. 2024), 1–27. doi:10.1145/3678518

[14] Tero Karras, Samuli Laine, and Timo Aila. 2019. A Style-Based Generator Architecture for Generative Adversarial Networks. *arXiv:1812.04948 [cs, stat]* (March 2019). http://arxiv.org/abs/1812.04948 arXiv: 1812.04948.

[15] Sage Kelly, Sherrie-Anne Kaye, and Oscar Oviedo-Trespalacios. 2023. What factors contribute to the acceptance of artificial intelligence? A systematic review. *Telematics and Informatics* 77 (2023), 101925.

[16] Jung Soo Lee. 2017. The Role of Sketches in Fashion Design -Focus on a Case Study of a Professional Designer's Process-. *Journal of Fashion Business* 21, 3 (2017), 58–66. doi:10.12940/jfb.2017.21.3.58 Publisher: The Korean Society of Fashion Business.

[17] Hyerim Park, Joscha Eirich, Andre Luckow, and Michael Sedlmair. 2024. "We Are Visual Thinkers, Not Verbal Thinkers!": A Thematic Analysis of How Professional Designers Use Generative AI Image Generation Tools. In *Nordic Conference on Human-Computer Interaction*. ACM, Uppsala Sweden, 1–14. doi:10.1145/3679318.3685370

[18] Robin Rombach, Andreas Blattmann, Dominik Lorenz, Patrick Esser, and Björn Ommer. 2022. High-Resolution Image Synthesis with Latent Diffusion Models. http://arxiv.org/abs/2112.10752 arXiv:2112.10752 [cs].

[19] Mathias Peter Verheijden and Mathias Funk. 2023. Collaborative Diffusion: Boosting Designerly Co-Creation with Generative AI. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems (CHI EA '23)*. Association for Computing Machinery, New York, NY, USA, 1–8. doi:10.1145/3544549.3585680

[20] Qiang Wang, Di Kong, Fengyin Lin, and Yonggang Qi. 2023. DiffSketching: Sketch Control Image Synthesis with Diffusion Models. doi:10.48550/arXiv.2305.18812 arXiv:2305.18812 [cs].

[21] Di Wu, Zhiwang Yu, Nan Ma, Jianan Jiang, Yuetian Wang, Guixiang Zhou, Hanhui Deng, and Yi Li. 2023. StyleMe: Towards Intelligent Fashion Generation with Designer Style. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, 1–16. doi:10.1145/3544548.3581377

[22] Lvmin Zhang, Anyi Rao, and Maneesh Agrawala. 2023. Adding Conditional Control to Text-to-Image Diffusion Models. In *2023 IEEE/CVF International Conference on Computer Vision (ICCV)*. IEEE, Paris, France, 3813–3824. doi:10.1109/ICCV51070.2023.00355

# A System Architecture

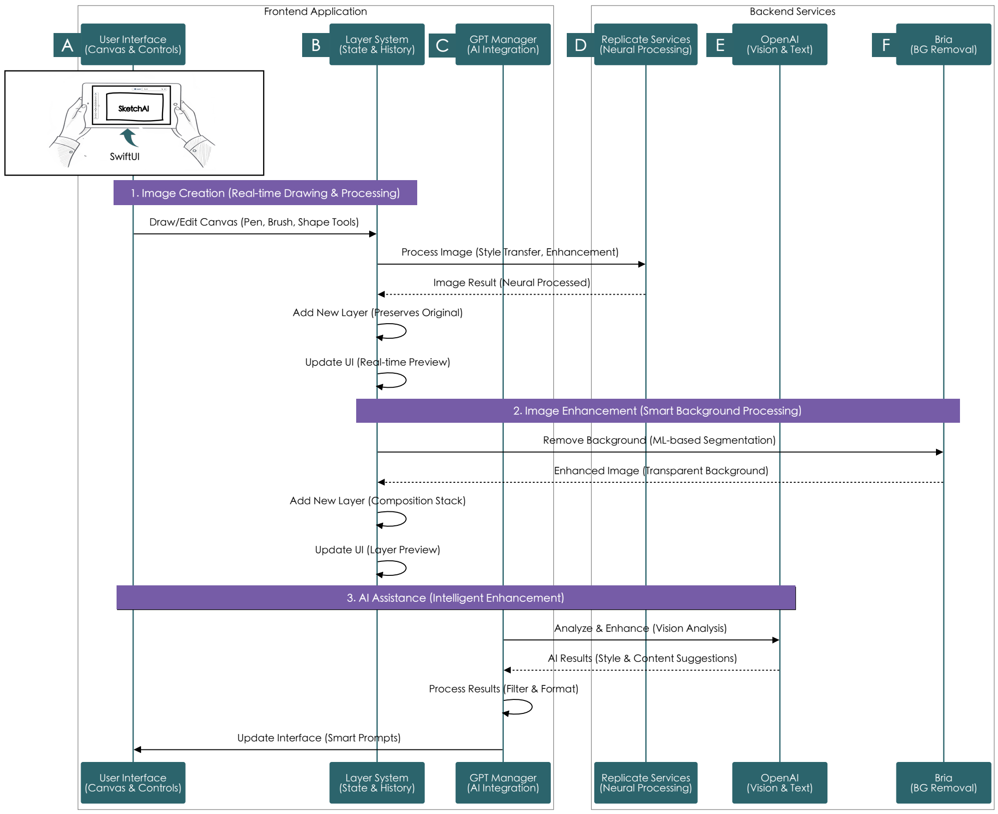


**Figure 5: System architecture with three operational flows: (1) Image Creation with real-time processing, (2) Background Processing for segmentation, and (3) Enhancement using GPT-4's capabilities. Each flow assists in the overall capabilities of the system while maintaining data consistency through the Layer System.**