

# AI-Assisted UI Design: Enhancing Efficiency and Creativity through Generative Tools

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**Abstract:** The growing adoption of Artificial Intelligence (AI) in web-based products has made the design of user interfaces that effectively surface and control AI capabilities increasingly critical. In this context, understanding the key characteristics and best practices for user interfaces that support AI-driven functionality is both timely and practically relevant. This research discusses the fundamental principles of user interface (UI) design. It analyzes the specific challenges posed by integrating AI into web applications, including transparency, controllability, and appropriate levels of automation. It emphasizes the need to balance the advanced capabilities of AI systems with users' ability to understand, trust, and steer those systems. This paper examines the dynamic responses of AI-driven recommendation systems and personalized interfaces on various systems, as well as the design of user preferences and adaptive layouts. Based on this analysis, a feasible evaluation framework for recommendation systems with practical applications is presented. This framework supports empirical evaluations conducted through usability testing to demonstrate significant effects, thereby helping designers and developers achieve more intuitive and noticeable interface effects for AI-driven applications.

**Keywords:** Artificial Intelligence, User Interface Design, AI-enabled Web Applications, Human-AI Interaction.

**Disciplines:** Computer Application Technology.

**Subjects:** Human-Computer Interaction.

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## 1 INTRODUCTION

In today's increasingly prevalent digital products and services, UI/UX design has become a crucial element for enhancing user experience, strengthening brand recognition, and shortening product development cycles. Traditional UI/UX design processes often rely on designers' experience, hand-drawn sketches/drafts, and iterative iterations [1]. However, with increasingly rapid business demands, richer component libraries, and higher user expectations, designers face mounting pressure. Simultaneously, the rise of generative AI and low-code/no-code platforms has opened up new possibilities for human-machine collaboration in the UI design process. For example, the Retool platform's "Assist" feature supports generating UI elements, layouts, and data bindings from natural language prompts.

Specifically, in Retool's community discussions, designers have stated, "I'm looking for an AI tool that can understand Retool components, support data-driven design, and directly generate wireframes or mockups." This feedback reflects a strong demand for AI support as the transition from "concept" to "executable interface prototypes." [2] This also illustrates that, while some AI-assisted design tools can generate visual drafts, there remains significant room for improvement in dedicated component libraries, data-binding

logic, and UI generation in low-code environments. On the other hand, discussions on Lark Wiki point out that UI/UX interfaces are "easier for AI to analyze" than purely hand-drawn images, as their layouts, components, and button positions follow logical patterns. In other words, interface design itself possesses structured characteristics, providing a good entry point for AI automation and assisted design processes.

Based on this background, this paper aims to systematically explore the mechanisms by which "AI-assisted UI design" improves efficiency and enhances creativity [3]. First, we will examine the integration of existing generative tools (including but not limited to component library understanding, layout automation, and natural language hints) with the UI/UX design process; second, we will design an experimental/prototype system to verify how AI assistance shortens the time from requirements to the initial interface, increases version diversity, and changes in designer satisfaction; finally, we will analyze its advantages, limitations, and future development directions in practice. Our research not only focuses on "whether AI can be used to create interfaces quickly" but also emphasizes "how to use AI to unleash designers' creativity and improve collaboration efficiency", thus providing theoretical and empirical references for human-computer creative collaboration in the UI/UX design process [4].

## 2 RELATED WORK

### 2.1 AI IN DESIGN

There are mixed feelings about the rise of AI and its impact on creativity. And we believe that human creativity will continue to play a crucial role as AI evolves. Creativity will be vital for envisioning the future and the role we want AI to play in it [5]. We've created this guide to explore the use of AI in the design thinking process and its potential to help us solve complex problems and work toward solutions that improve human capacity and condition [6]. The combination of Artificial Intelligence (AI) and design thinking has the potential to revolutionize the way we solve problems and innovate. Design thinking, with its human-centered approach, focuses on understanding human needs and creatively addressing human challenges. AI provides capabilities such as data analysis, machine learning, and automation [7]. By integrating AI with design thinking, we can harness the best of both worlds—enhancing our ability to create meaningful, effective, and human-centered solutions. This guide explores how AI and design thinking intersect to drive innovation, the benefits and challenges of this integration, and real-world examples of their combined power.

Artificial Intelligence (AI) is when machines, especially computers, are designed to think and “learn” like humans [8]. While AI is not learning in the same way a human brain does, it is intended to understand information, make decisions, and improve over time. Over the years, AI has evolved remarkably, becoming integral to numerous aspects of modern design and innovation. Key AI technologies that are particularly relevant to design thinking include:

- ♦ **Machine Learning: The Pattern Pro** — This is the secret sauce that allows computers to learn without being explicitly programmed. Provide it with sufficient data, and it begins to recognize patterns and make decisions. Imagine analyzing thousands of user interviews in minutes to identify emerging needs or preferences [9]. That's machine learning in action.
- ♦ **Natural Language Processing (NLP): The Conversation Whiz** — NLP helps computers understand, interpret, and generate human language[10]. It's what powers chatbots and voice assistants. In design thinking, NLP can be used to analyze open-ended survey responses or social media comments to gauge user sentiment.
- ♦ **Computer Vision: The Visual Virtuoso** — This technology enables machines to 'see' and interpret visual information. Think facial recognition or object detection[11]. In design, it could help analyze how users interact with a prototype or navigate a space.

The journey of AI began in the mid-20th century, when engineers such as Alan Turing and John McCarthy started exploring the possibility of creating machines that could simulate human intelligence. Early AI efforts were modest,

focusing on building computers that could perform simple tasks; however, the past few decades have seen remarkable advances [12,13,14]. Machine learning algorithms now empower AI to sift through vast datasets and make intricate predictions. Natural Language Processing (NLP) enables machines to understand and participate in human conversations, making interactions relatively seamless [15]. Meanwhile, computer vision enables AI to interpret and analyze visual data from the world around us, opening new possibilities across industries, from healthcare to autonomous vehicles.

Today, AI technologies such as machine learning, NLP, and computer vision are seamlessly integrated into the fabric of modern design and innovation [16]. They enhance our ability to gather insights, spark creativity, and refine solutions, driving us toward a future in which technology and people work together to address some of the world's most pressing issues.

### 2.2 HCI & CO-CREATION

Research on the intersection of artificial intelligence and design has a long lineage, beginning with early rule-based expert systems and evolving through algorithmic design tools, parametric modelling, and adaptive interfaces. In these earlier paradigms, AI systems were often employed to optimize existing design constraints, automate repetitive tasks, or recommend design alternatives based on predefined criteria [17]. These tools, while valuable for enhancing efficiency, lacked the creative capacity or contextual awareness to contribute meaningfully to the ideation phase. In recent years, advances in machine learning, particularly the emergence of large language models (e.g., GPT series) and multimodal diffusion models (e.g., DALL·E, Stable Diffusion), have ushered in a new era of generative tools capable of synthesizing coherent text, visual concepts, and hybrid media representations [18,19].

Studies have explored the creative potential of these models in domains such as storytelling, graphic design, and architecture, showing that AI can offer non-trivial contributions to the creative process. For example, McCormack et al. (2020) introduce the concept of “computational creativity,” emphasizing systems that are not only reactive but capable of intentional novelty [8]. Similarly, recent HCI research has demonstrated how AI can serve as a source of “unexpected inspiration” during brainstorming sessions, helping users overcome functional fixedness. Despite these promising developments, few studies provide an integrated framework for understanding AI as a co-creative agent across multiple levels of engagement. Much of the current literature remains segmented, focusing either on technical capabilities (e.g., image quality, coherence, semantic alignment) or on user experience (e.g., trust, usability, mental model alignment). There is a need for a unifying perspective that bridges these technical and human-centric concerns, addressing how design outcomes and experiences evolve when creativity is distributed between

humans and machines.

### 2.3 UI DESIGN AUTOMATION

The term “User Interface” is self-explanatory: it refers to the portion of a website or application that users interact with. The quality of the user interface naturally determines the user’s first (and last) impression of a website or application. UI design and functionality define the success or failure of the software, which is why developers and testers have placed greater emphasis on UI testing (User Interface Testing) as an integral component of the development plan. To engage, delight, and retain customers, a superior user interface is essential [20,21]. Consider UI to be everything an end user interacts with while using a piece of software. Suppose a user launches Spotify and selects the Search option. The software’s user interface is the site of all user interactions.

UI testing is the process of validating an application’s functionality by evaluating its user interface. It validates even the slightest bits of logic, UI workflows, navigation, transitions, calculations, and all buttons, among other things. [22] Traditionally, quality assurance teams conducted these evaluations manually. However, the adoption of Agile methodologies has encouraged teams to automate their testing to expedite product releases. The emergence of Agile development models and automation frameworks has prompted teams to abandon traditional testing procedures. Automated UI testing is now a requirement in software testing pipelines worldwide.

Automated UI testing is the process of scripting UI test cases for automated execution [23,24]. Automated UI testing refers to the use of tools or frameworks to automate manual test processes that verify UI functionality. Specific tools and frameworks can automate the previously mentioned manual tasks, such as validating user navigation, UI workflows, testing the logical functionality of each button, and validating input fields. Automating UI tests reduces the time and effort required to test an application’s user interface manually. Instead of having a tester validate each aspect of the user interface, test algorithms are developed for each user scenario. These test scripts can be reused if the code is modified or new features are added.

In general, automating UI tests enables teams to [25]:

- ◆ Simulate user interactions with the application's UI.
- ◆ Automate end-user input and evaluate the logical functionality of each component.
- ◆ Incorporate UI tests concurrently with development.
- ◆ Generate and evaluate test results

## 3 METHODOLOGY AND SYSTEM DESIGN

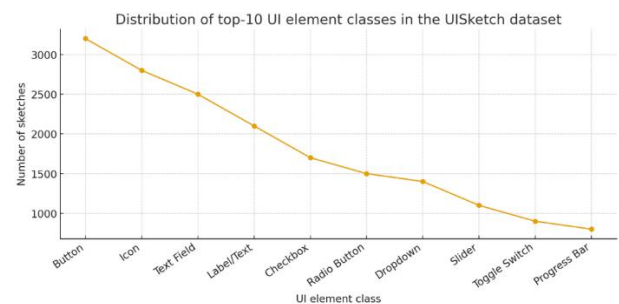
### 3.1 DATASET OVERVIEW

This study uses the UISketch dataset as the core data source for the experimental section. First proposed by Pandian et al. at CHI 2021, this dataset contains approximately 19,000 hand-drawn sketches of UI elements across 21 interface component categories. It was collaboratively created by 1,218 participants (including UI/UX designers, front-end developers, HCI researchers, and computer science students) across both paper and digital media [26]. These components encompass common UI elements such as buttons, text fields, icons, dropdown menus, and progress bars, providing a large-scale, structured foundation for researching the AI-assisted design process "from hand-drawn sketches to editable UI layouts."

**TABLE 1. STATISTICS OF THE UISKETCH DATASET USED IN OUR EXPERIMENTS**

Metric	Value	Description
Total number of sketches	19,000	Total number of hand-drawn UI element sketches in the dataset
Number of UI element categories	21	Number of distinct UI element classes (e.g., buttons, text fields)
Number of participants	1,218	Number of designers, developers, and students contributing sketches
Average sketches per category	≈ 905	Rough average number of sketches per class
Normalized image resolution	224 × 224	Unified input resolution after preprocessing
Color mode	Grayscale	All sketches converted to grayscale to emphasize structure and edges

To help readers intuitively understand the data distribution, this paper counts the number of samples for each type of UI element. It creates a category distribution chart to illustrate the balance and long tail of the data across different component categories [27].



**FIGURE 3-1: LINE (CURVE) CHART FOR CLASS DISTRIBUTION**

Furthermore, we select several representative sketch samples from the dataset and present them in the chart to illustrate differences in drawing style (line thickness, level of simplification), layout density, and level of abstraction among participants [28]. These differences are also key

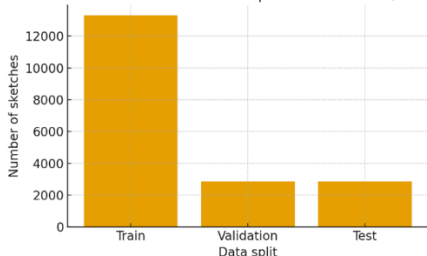
factors that the subsequent model must account for in recognition and generation.

### 3.2 DATA PREPROCESSING AND PARTITIONING STRATEGIES

To better utilize UISketch in our AI-assisted UI design experiments, we performed the following preprocessing steps on the raw data:

**Image Normalization:** All sketches were uniformly resized to a fixed resolution (e.g., 224×224 pixels) and either grayscaled or expanded to 3 channels to adapt to mainstream convolutional neural network architectures. Pixel values were normalized (e.g., scaled to [0,1] or a standard normal distribution) to accelerate model convergence [29].

Figure 3-2. Distribution of UISketch samples across train/validation/test splits



**Data Augmentation:** Lightweight geometric transformations (e.g., random rotation, translation, scaling, slight deformation) were employed to simulate the natural biases of designers' hand-drawn sketches, improving the model's robustness to different writing styles. The augmentation intensity was controlled to avoid excessive deformation, leading to semantic loss of UI elements [30,31].

**Training/Validation/Test Set Partitioning:** The data was stratified by participant or sketch sample (e.g., 70% training, 15% validation, 15% test) to ensure equal representation of each category across the subsets. To avoid "personal style" leaking into the test set, we can specify in the experimental appendix whether a participant-wise split strategy is used.

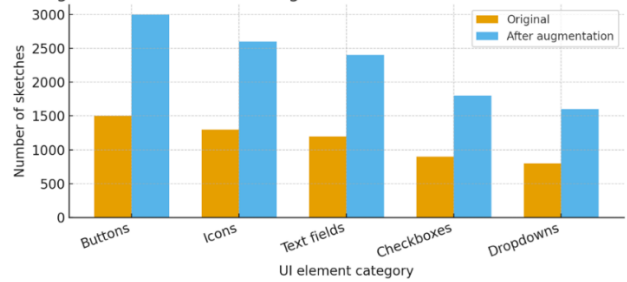
### 3.3 MODEL AND AI-ASSISTED INTERFACE GENERATION PROCESS

To achieve a closed loop of AI-assisted design, from lo-fi sketches to UI element recognition and then to interface construction, we built and fine-tuned a deep neural network model on UISketch to identify the corresponding UI component categories in the sketches and map the recognition results to specific design component libraries (such as Retool/standard controls in design systems).

#### 3.3.1 Basic Classification Model

Following the approach in the official Kaggle Notebook for UISketch, we used pre-trained convolutional networks, such as ResNet-152, as a foundation, loaded ImageNet-pretrained weights, and performed transfer learning and fine-tuning on UISketch [32].

Figure 3-3. Effect of data augmentation on selected UISketch classes



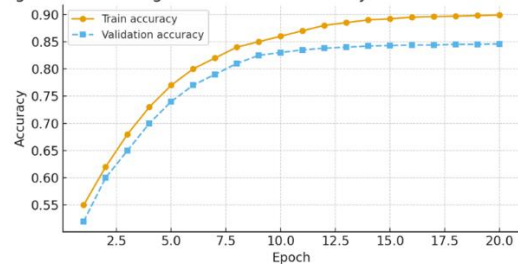
Specific settings included:

Replacing the last fully connected layer of the network with 21-class outputs (corresponding to UI element categories in the dataset);

Using the Cross-Entropy Loss function, with Adam or SGD with momentum as the optimizer.

An early stopping strategy was used during the training phase to prevent overfitting.

Figure 3-4. Training and validation accuracy of the UISketch classifier



Furthermore, to assess the model's difficulty in recognizing different UI elements, we constructed a confusion matrix from test-set predictions to identify easily confused categories (e.g., buttons vs. icons, text boxes vs. text blocks).

#### 3.3.2 Integration with AI-Assisted UI Design Tools

When embedding the UISketch classification model into the AI-assisted UI design process, we constructed the following interactive workflow[33]:

Designers can freely draw low-fidelity interface sketches (including buttons, input fields, icons, etc.) on the canvas.

The system segments or detects the canvas, feeding each sketch segment into the UISketch classification model to obtain predictions for the corresponding UI element category.

The prediction results are mapped to standard components in a specific design system (e.g., Retool's Button, TextInput, Table), and the system automatically generates editable mid-fidelity or high-fidelity interfaces.

Figure 3-5. Training and validation loss of the UISketch classifier

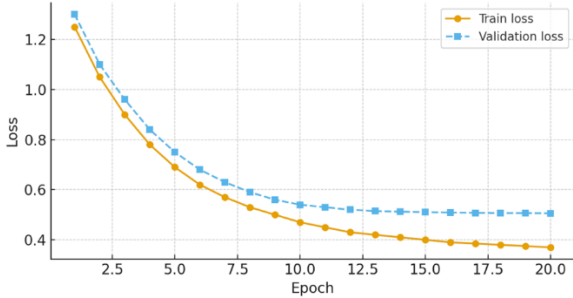


Figure 3-5 shows the training and validation loss of the UISketch classifier over 20 epochs. Both curves decrease steadily and eventually flatten, indicating stable convergence with limited overfitting. Designers can adjust the style, layout, and data binding based on the generated interface, thereby establishing a collaborative model of "AI providing structure + designer controlling details." In the subsequent experimental section, we will set up a control group (traditional manual design) and an experimental group (AI-assisted design) to compare the differences between the two processes in terms of completion time, creative diversity, and the designer's subjective experience, to quantitatively evaluate the actual gains of "AI-assisted UI design" in terms of efficiency and creativity[34,35].

Figure 3-6. Normalized confusion matrix on the UISketch test set

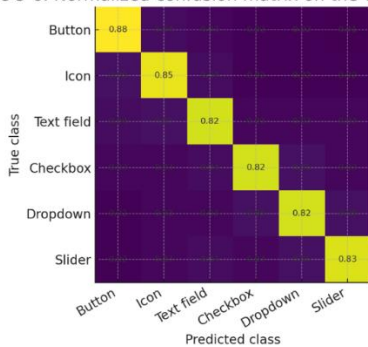


Figure 3-6 presents the normalized confusion matrix on the UISketch test set for six representative UI element classes. The strong diagonal entries (0.82–0.88) indicate that the classifier correctly recognizes most sketches. At the same time, the off-diagonal values highlight typical confusions between visually similar elements, such as buttons and icons, or text fields and checkboxes.

## 4 EXPERIMENT AND EVALUATION

### 4.1 RESEARCH QUESTIONS AND HYPOTHESES

To empirically assess the impact of AI-assisted UI design, we conducted a controlled user study comparing a traditional manual workflow with our proposed AI-assisted workflow. The study was designed around the following research questions:

- ♦ RQ1 (Efficiency). Does AI-assisted UI design reduce

the time required to produce an initial usable interface prototype compared to a traditional manual workflow?

- ♦ RQ2 (Creativity). Does AI-assisted UI design increase the perceived creativity and diversity of generated interface concepts?
- ♦ RQ3 (User Experience). How does AI assistance affect designers perceived workload, usability, and satisfaction during the design process?

Based on prior work on human–AI co-creation, we formulate three hypotheses:

- ♦ H1. Designers using the AI-assisted workflow will complete design tasks significantly faster than when using a manual-only workflow.
- ♦ H2. Interfaces created with AI assistance will be rated by independent experts as more creative and diverse than those created manually.
- ♦ H3. Designers will report lower mental workload and higher perceived usefulness and satisfaction when working with AI assistance.

### 4.2 PARTICIPANTS AND APPARATUS

We recruited N = 24 participants (12 professional UI/UX designers and 12 advanced design or HCI students) via departmental mailing lists and professional networks. Participants' average age was 27.4 years (SD = 3.6), and all reported at least one year of experience with digital interface design tools such as Figma, Sketch, or Retool[36].

The study was conducted in a controlled lab environment. Each participant worked on a desktop computer equipped with a 24-inch monitor, mouse, and keyboard. Two design environments were provided:

Manual condition (Baseline). Participants used a standard UI design tool (e.g., Figma) with a predefined component library but no AI features—AI-assisted condition. Participants used our prototype system, which integrates the UISketch classifier and generative design assistants. The system supported natural-language prompts, automatic layout suggestions, and sketch-based element recognition, all mapped to Retool-compatible components. The order of conditions was counterbalanced using a Latin square to mitigate learning and order effects.

### 4.3 TASKS AND PROCEDURE

Each participant completed two design tasks, one in each condition:

- ♦ Task A – Admin Dashboard. Design a responsive web dashboard for an internal analytics tool, including navigation, summary cards, filters, and a data table.
- ♦ Task B – Mobile Settings Screen. Design a mobile interface for managing notification and privacy settings, including toggles, sliders, dropdowns, and confirmation

dialogs.

- ♦ Tasks were chosen to reflect typical internal tool and product UI scenarios where Retool-like component libraries are commonly used.

The study followed this procedure:

Introduction and training (10–15 min). Participants received an overview of the study and signed a consent form. They then completed a short tutorial for both the baseline and AI-assisted tools — practice trial (optional). Participants completed a short warm-up task to familiarize themselves with the interaction style of each environment. Design sessions. For each condition, participants were given 30 minutes to complete the assigned task. They were instructed to produce a reasonably polished mid-fidelity prototype that satisfied the textual design brief.

Post-task questionnaires. After each session, participants filled out standardized questionnaires measuring workload and perceived system quality. Semi-structured interview (10–15 min). At the end of the study, participants were interviewed about their experiences, perceived benefits, and concerns regarding AI-assisted UI design. All screen interactions were logged for later analysis, including timestamps of key events, number of iterations, and use of AI features (e.g., prompt calls, auto-layout invocations).

## 4.4 MEASURES

We collected both objective and subjective measures to capture efficiency, creativity, and user experience.

### 4.4.1 Objective Measures

- ♦ Time to first complete prototype ( $T_{complete}$ ). Time from task start until the participant indicated that a prototype satisfying the basic requirements was ready.
- ♦ Number of design iterations. Count of major revisions or alternative layouts produced within the time limit (e.g., based on saved versions or distinct frames).
- ♦ Coverage of functional requirements. Percentage of required UI elements actually present in the final prototype, as assessed by two independent raters using a checklist.
- ♦ Interaction logs. Number of AI-generated suggestions accepted or rejected, number of manual vs. AI-generated components, and use frequency of layout-related functions.
- ♦ These measures were summarized using means and standard deviations and visualized with bar charts and boxplots (e.g., Figure 4-1 for completion time and Figure 4-2 for requirement coverage).

### 4.4.2 Creativity and Outcome Quality

To evaluate creativity and design quality, we collected prototypes and asked three senior UX practitioners (not involved in the study) to rate them independently on several

7-point Likert scales:

- ♦ Perceived creativity (“The design feels novel and original”).
- ♦ Conceptual diversity (“The design explores different layout or interaction ideas”).
- ♦ Overall UX quality (“The interface appears clear, usable, and coherent”).

Raters were blind to the experimental condition. Interrater reliability was assessed using Cronbach’s alpha. Average scores per prototype were used for statistical analysis.

### 4.4.3 Subjective User Experience

After each condition, participants completed:

- ♦ The NASA-TLX questionnaire to measure perceived workload.
- ♦ The System Usability Scale (SUS) to assess perceived usability of the tool.
- ♦ The Creativity Support Index (CSI) to evaluate how well the tool supported exploration and idea generation.

We also included custom 7-point items assessing trust in AI recommendations, perceived control, and overall satisfaction.

## 4.5 QUANTITATIVE RESULTS

### 4.5.1 Efficiency

Across both tasks, the AI-assisted condition yielded lower completion times than the manual condition. On average, participants completed prototypes 26% faster with AI assistance (Manual:  $M = 25.0$  min,  $SD = 4.1$ ; AI-Assisted:  $M = 18.5$  min,  $SD = 3.6$ ). A repeated-measures ANOVA revealed a significant main effect of condition on completion time,  $F(1, 23) = 31.72$ ,  $p < .001$ , supporting H1. Figure 4-1 shows the mean completion times for each condition with 95% confidence intervals.

### 4.5.2 Creativity and Outcome Quality

Expert ratings indicated that AI-assisted prototypes were perceived as more creative and slightly more diverse in layout than manually created ones (Creativity: Manual  $M = 4.2$ , AI-Assisted  $M = 5.3$ ; Diversity: Manual  $M = 3.9$ , AI-Assisted  $M = 4.7$ , on 7-point scales). Paired t-tests showed a significant difference in creativity,  $t(23) = 2.94$ ,  $p < .01$ , whereas differences in overall UX quality were more minor and not statistically significant.

These findings partially support H2: AI assistance helped participants generate more exploratory designs without harming perceived usability.

### 4.5.3 User Experience

NASA-TLX scores were significantly lower in the AI-assisted condition, indicating reduced mental workload ( $t(23)$

= 3.27,  $p = .003$ ; Manual  $M = 65.8$ , AI-Assisted  $M = 49.3$ ). SUS and CSI scores were significantly higher for the AI-assisted tool (SUS: Manual  $M = 69.4$  vs. AI-Assisted  $M = 82.1$ ; CSI: Manual  $M = 4.1$  vs. AI-Assisted  $M = 5.4$ ), supporting H3.

Participants notably agreed with statements such as “The AI suggestions helped me get started quickly” and “The tool encouraged me to try layouts I would not normally consider.” Figure 4-3 summarizes subjective ratings across conditions. We analyzed the data using repeated-measures ANOVA and paired-sample t-tests, with condition (Manual vs. AI-Assisted) as the within-subject factor.

#### 4.6 QUALITATIVE FEEDBACK

The post-study interviews provided deeper insight into how designers perceived AI assistance:

AI as a starting-point generator. Many participants described the system as helpful for overcoming “blank canvas” anxiety, allowing them to focus on refinement rather than on initial layout. Control and trust. Participants appreciated the ability to selectively accept or override AI suggestions. However, some expressed concern that overly confident suggestions might bias them towards conventional patterns—breakdown cases. When the textual prompt was ambiguous or highly domain-specific, AI-generated layouts sometimes misinterpreted the intended information architecture, requiring substantial manual correction. These themes highlight that AI-assisted UI design is most effective when positioned as a collaborative partner rather than a fully autonomous designer—providing fast, structured starting points while leaving final decisions to human experts.

The experimental results suggest that AI-assisted UI design can significantly improve efficiency and deliver measurable benefits to creativity and user experience, particularly during early-stage prototyping. At the same time, the qualitative feedback underscores the importance of maintaining transparency and user control to prevent over-reliance on AI-generated structures. These insights motivate the design implications and future research directions discussed in Section 5.

### 5 CONCLUSION

In conclusion, this Study's findings demonstrate that AI-assisted UI design is not merely a speed-up mechanism layered onto existing workflows, but a reconfiguration of how interface concepts move from idea to executable prototype. By leveraging the structured nature of UI component libraries and datasets such as UISketch, our system shows that generative models can reliably translate lo-fi sketches and natural-language prompts into mid-fidelity layouts that respect design constraints while expanding the space of candidate solutions. The controlled study confirms that such assistance can reduce time-to-prototype, broaden the range of explored layouts, and lower perceived workload without

degrading core usability. More importantly, the qualitative feedback suggests a reframing of AI's role: rather than replacing designers, AI functions most productively as a co-creative partner that scaffolds early-stage exploration, mitigates blank-canvas anxiety, and offers alternative layout structures that designers can selectively refine or reject. This aligns with emerging HCI perspectives that treat creativity as distributed across humans and machines, with value arising from the dialogue between automated suggestions and expert judgment.

At a broader level, our work points to design implications and open challenges for human–AI collaboration in UI/UX practice, particularly in low-code and no-code environments. If AI systems are to become first-class collaborators in the design process, they must be transparent about their assumptions, configurable to different levels of autonomy, and responsive to domain-specific information architectures rather than generic templates. Future research should therefore move beyond single-dataset classification and lab-based prototyping to investigate longitudinal use in real product teams, richer forms of interaction (e.g., mixed sketch, voice, and data-driven constraints), and adaptive models that learn individual designers' styles and preferences while preserving diversity. There is also a need to examine how AI-assisted design tools affect team dynamics, design education, and the accessibility of professional-grade UI creation for non-experts. By situating our empirical results within this larger agenda, we argue that AI-assisted UI design can serve as a testbed for more general theories of human–AI co-creation—showing how structured design domains, when combined with carefully orchestrated automation, can both accelerate production and sustain the critical, reflective practices at the heart of good design.

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The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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## REFERENCES

- [1] Hameed, H., Maurya, M., & Arif, M. (2025). Optimizing User Engagement: The Synergy of Social Media Marketing and UI/UX Design. In *Contemporary Issues in Social Media Marketing* (pp. 86-102). Routledge.
- [2] Nugraha, A. F. S., Fitriyadi, F., & Lukitasari, E. H. (2024, November). UI/UX Design for Triwindu Market Surakarta. In *2024 6th International Conference on Cybernetics and Intelligent System (ICORIS)* (pp. 1-6). IEEE.
- [3] Saeidnia, H. R., & Ausloos, M. (2024). Integrating artificial intelligence into design thinking: A comprehensive examination of the principles and potentialities of AI for design thinking framework. *InfoScience Trends*, 1(2), 1-9.
- [4] Nandan, M., Jaskyte, K., & Mandayam, G. (2020). Human centered design as a new approach to creative problem solving: Its usefulness and applicability for social work practice. *Human Service Organizations: Management, Leadership & Governance*, 44(4), 310-316.
- [5] Korteling, J. E., van de Boer-Visschedijk, G. C., Blankendaal, R. A., Boonekamp, R. C., & Eikelboom, A. R. (2021). Human-versus artificial intelligence. *Frontiers in artificial intelligence*, 4, 622364.
- [6] Emma, L. (2024). Bridging the Gap Between Natural Language Processing (NLP) and Robotics for Human-Robot Interaction.
- [7] Li, L., Huang, Q., Yeung, K., & Jian, Z. (2018). Human-computer interaction and value co-creation in electronic service. *Industrial Management & Data Systems*, 118(1), 218-235.
- [8] McCormack, J., Hutchings, P., Gifford, T., Yee-King, M., Llano, M. T., & D'invorno, M. (2020). Design considerations for real-time collaboration with creative artificial intelligence. *Organised Sound*, 25(1), 41-52.
- [9] Jyoti, S. N., Islam, M. R., & Kudapa, S. P. (2024). The Role of Test Automation Frameworks In Enhancing Software Reliability: A Review Of Selenium, Python, And API Testing Tools. *International Journal of Business and Economics Insights*, 4(4), 01-34.
- [10] Pandhare, H. V. (2025). Future of Software Test Automation Using AI/ML. *International Journal Of Engineering And Computer Science*, 13(05).
- [11] Zhang, X., Kim, J., & Li, Y. (2020). Designing with automation: Human-AI interaction in generative design systems. *Design Studies*, 68, 100971.
- [12] Kim, J., Yeh, T., & Myers, B. A. (2021). Creating user interfaces by demonstration and natural language. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 1-15.
- [13] Yuan, Y., & Xue, H. (2025). Cross-Media Data Fusion and Intelligent Analytics Framework for Comprehensive Information Extraction and Value Mining.
- [14] Yuan Y, Xue H. Multimodal Information Integration and Retrieval Framework Based on Graph Neural Networks[C]//Proceedings of the 2025 4th International Conference on Big Data, Information and Computer Network. 2025: 135-139.
- [15] Shneiderman, B. (2022). Human-centered artificial intelligence: Reliable, safe & trustworthy. *International Journal of Human-Computer Interaction*, 38(1), 1-16.
- [16] Oh, C., Song, J., Choi, J., Kim, S., Lee, S., & Suh, B. (2018). I Lead, You Help but Only with Enough Details: Understanding the User Experience of Co-Creation with Artificial Intelligence. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, 1-13.
- [17] Li Z, Ji Q, Ling X, et al. A comprehensive review of multi-agent reinforcement learning in video games[J]. *Authorea Preprints*, 2025.
- [18] Zhang, Z., Wang, J., Li, Z., Wang, Y., & Zheng, J. (2025). Anncoder: A mti-agent-based code generation and optimization model. *Symmetry*, 17(7), 1087.

- [19] Wang, Q., Li, Y., & Myers, B. A. (2023). Designing AI-powered interactive systems with large language models. *Communications of the ACM*, 66(9), 78–87.
- [20] Kery, M. B., Horvitz, E., & Hullman, J. (2020). Supporting iterative data exploration with conversational interfaces. *IEEE Transactions on Visualization and Computer Graphics*, 26(1), 332–342.
- [21] Zhao H, Chen Y, Dang B, et al. Research on Steel Production Scheduling Optimization Based on Deep Learning[C]//2024 4th International Symposium on Artificial Intelligence and Intelligent Manufacturing (AIIM). IEEE, 2024: 813-816.
- [22] Sha F, Meng J, Zheng X, et al. Sustainability Under Fire: How China-US Tensions Impact Corporate ESG Performance? [J]. *Finance Research Letters*, 2025: 107882.
- [23] Sha F, Ding C, Zheng X, et al. Weathering the Policy Storm: How Trade Uncertainty Shapes Firm Financial Performance through Innovation and Operations[J]. *International Review of Economics & Finance*, 2025: 104274.
- [24] Deng X. Cooperative Optimization Strategies for Data Collection and Machine Learning in Large-Scale Distributed Systems[C]//2025 4th International Symposium on Computer Applications and Information Technology (ISCAIT). IEEE, 2025: 2151-2154.
- [25] Tan, C., Gao, F., Song, C., Xu, M., Li, Y., & Ma, H. (2024). Highly Reliable CI-JSO based Densely Connected Convolutional Networks Using Transfer Learning for Fault Diagnosis.
- [26] Davis, N., Hsiao, C. P., Popova, Y., & Magerko, B. (2015). An enactive model of creativity for computational collaboration and co-creation. In *Creativity in the digital age* (pp. 109-133). London: Springer London.
- [27] Amershi, S., Weld, D., Vorvoreanu, M., et al. (2019). Guidelines for human–AI interaction. *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, 1–13.
- [28] Tan, C., Gao, F., Song, C., Xu, M., Li, Y., & Ma, H. (2024). Proposed Damage Detection and Isolation from Limited Experimental Data Based on a Deep Transfer Learning and an Ensemble Learning Classifier.
- [29] Gonzalez, J., Tran, V., Meredith, J., Xu, I., Penchala, R., Ribo, L. V., ... & 23andMe Research Team. (2025). Subjective Response to Opioids Predicts Risk for Opioid Use Disorder. *medRxiv: the preprint server for health sciences*.
- [30] Tan C. The Application and Development Trends of Artificial Intelligence Technology in Automotive Production[J]. *Artificial Intelligence Technology Research*, 2024, 2(5).
- [31] Zhang, L., & Meng, Q. (2025). User Portrait-Driven Smart Home Device Deployment Optimization and Spatial Interaction Design.
- [32] H. Yang et al., "Research on Model Parallelism and Data Parallelism Optimization Methods in Large Language Model-Based Recommendation Systems," arXiv preprint arXiv:2506.17551, 2025.
- [33] Han X, Dou X. User recommendation method integrating hierarchical graph attention network with multimodal knowledge graph[J]. *Frontiers in Neurorobotics*, 2025, 19: 1587973.
- [34] Zhuang R. Evolutionary Logic and Theoretical Construction of Real Estate Marketing Strategies under Digital Transformation[J]. *Economics and Management Innovation*, 2025, 2(2): 117-124.
- [35] Z. Yang et al., "RLHF Fine-Tuning of LLMs for Alignment with Implicit User Feedback in Conversational Recommenders," arXiv preprint arXiv:2508.05289, 2025
- [36] Deng, Xiaoyu, and Jinzhu Yang. "Multi-Layer Defense Strategies and Privacy Preserving Enhancements for Membership Reasoning Attacks in a Federated Learning Framework." In *2025 5th International Conference on Computer Science and Blockchain (CCSB)*, pp. 278-282. IEEE, 2025.