Generative Interfaces for Language Models

Jiaqi Chen*, **Yanzhe Zhang***, **Yutong Zhang, Yijia Shao, Diyi Yang**
Stanford University

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Abstract

Large language models (LLMs) are increasingly seen as assistants, copilots, and consultants, capable of supporting a wide range of tasks through natural conversation. However, most systems remain constrained by a linear request-response format that often makes interactions inefficient in multi-turn, information-dense, and exploratory tasks. To address these limitations, we propose **Generative Interfaces** for Language Models, a paradigm in which LLMs respond to user queries by proactively generating user interfaces (UIs) that enable more adaptive and interactive engagement. Our framework leverages structured interface-specific representations and iterative refinements to translate user queries into task-specific UIs. For systematic evaluation, we introduce a multidimensional assessment framework that compares generative interfaces with traditional chat-based ones across diverse tasks, interaction patterns, and query types, capturing functional, interactive, and emotional aspects of user experience. Results show that generative interfaces consistently outperform conversational ones, with up to a 72% improvement in human preference. These findings clarify when and why users favor generative interfaces, paving the way for future advancements in human-AI interaction. Data and code are available at https://github.com/SALT-NLP/GenUI.

1 Instruction

A longstanding goal in computing is to design systems that not only respond to users but also adapt by dynamically reshaping interfaces to facilitate users' interaction and help them achieve their goals (Apple Inc., 1987; Lyytinen & Yoo, 2002). While recent advances in large language models (LLMs) have brought us closer to this vision by enabling flexible natural language understanding, the dominant interaction paradigm, which we call the conversational UI, remains static and linear: most LLM outputs are still rendered as long blocks of text, regardless of task complexity or user preference, limiting the model's ability to support the diverse ways users seek to learn, explore, and interact. At the same time, state-of-the-art LLMs have shown remarkable capabilities in automatically generating high-quality, functional webpages from sketches, queries, or natural language descriptions (Si et al., 2024; Li et al., 2024; Xiao et al., 2024). Together, these developments raise an exciting research question: **How can LLMs go beyond conversational interfaces to enable adaptive, goal-driven interactions that meaningfully serve human needs?**

In this work, we introduce **Generative Interfaces**, a new paradigm that differs from conversational UIs. Rather than delivering static text responses within a predefined chatbot window, Generative Interfaces dynamically create entirely new interface structures that adapt to users' specific goals and interaction requirements. While recent tools like OpenAI's Canvas (OpenAI, 2024a) and Claude's Artifacts (Anthropic, 2024) enhance user interaction by providing dedicated workspaces for documents, code, and visualizations, our approach extends this vision by supporting deeper engagement and enabling richer, task-specific experiences. For example, as shown in Figure 1, when users pose questions such as "*I want to understand neural networks*" or "*How can I learn piano effectively?*", conversational interfaces typically return long blocks of text. In contrast, Generative Interfaces transform these queries into an interactive neural network animation or a piano practice tool that offers real-time feedback. This paradigm shift presents two key challenges: (1) building the infrastructure to generate user interfaces on the fly in response to users' queries, and (2) rigorously evaluating whether such generated interfaces actually improve user experience.

To address the first challenge, our framework introduces a **structured interface-specific representation** coupled with an **iterative refinement** procedure. The structured representation enables more controllable and interpretable generation by explicitly modeling high-level interaction flows, interface state transitions, and component dependencies, which we formalize using finite state machines (Shehady & Siewiorek, 1997; Wagner et al., 2006). The iterative refinement procedure further enhances output quality by prompting LLMs to generate query-specific evaluation rubrics and repeatedly refine interface candidates through generation-evaluation cycles until the system converges on a polished, context-appropriate solution. To address the second challenge, we establish a systematic evaluation framework for
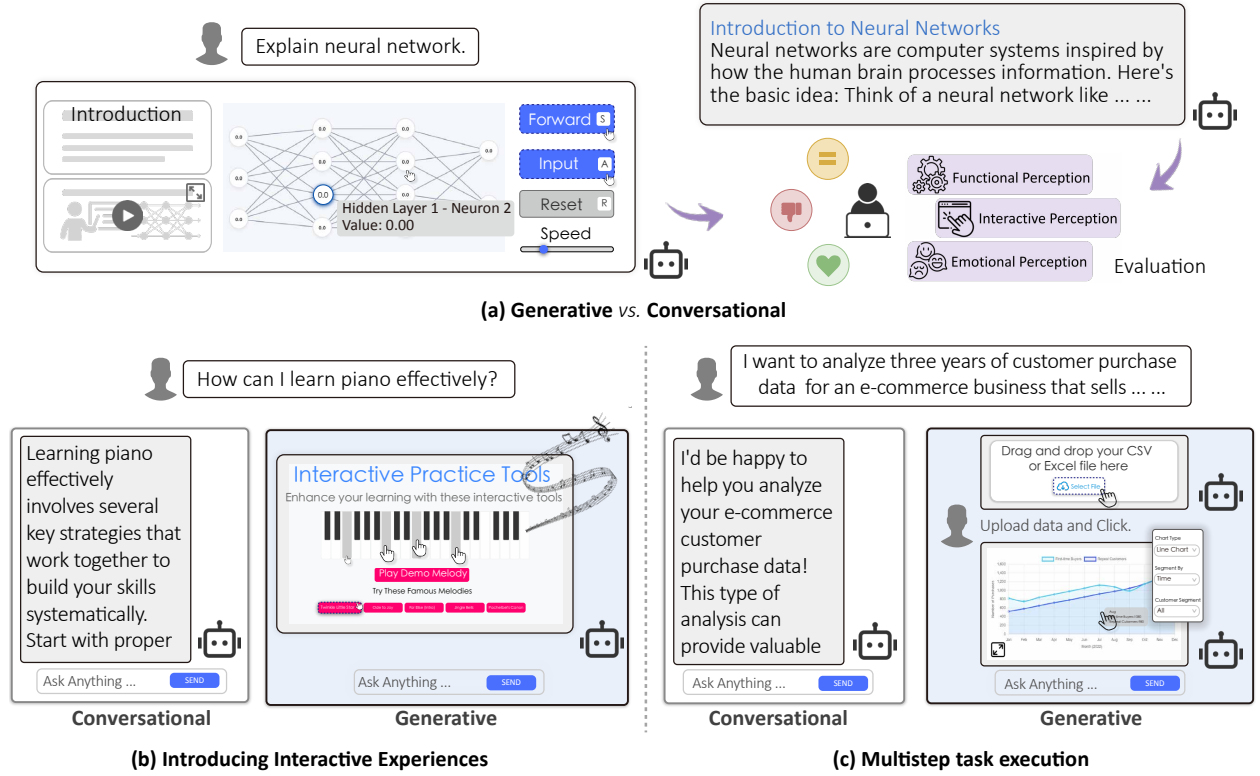
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*Equal contribution.

Figure 1: **Generative Interfaces compared to conversational interfaces.** (a) Conceptual framework showing how Generative Interfaces create structured, interactive experiences rather than static text responses, evaluated along functional, interactive, and emotional dimensions. (b–c) Example queries illustrate how Generative Interfaces transform user input into adaptive tools—such as interactive learning aids or multistep workflows—providing clearer organization and richer interactivity than conversational responses.

assessing language model interfaces across three key dimensions: functionality, interactivity, and emotional perception (Hartmann et al., 2008; Nielsen et al., 2012; Duan, 2025). Specifically, we construct a diverse prompt suite, **U**ser **I**nterface e**X**perience (UIX), that strategically covers diverse domains and prompt types to reflect real-world usage scenarios (Tamkin et al., 2024). For each user query, we recruit experienced annotators to interact with different interfaces and conduct pairwise comparisons. Beyond this fixed prompt suite, we further conduct a complementary evaluation involving real users and their self-reported queries, which substantiates the advantages of generative interfaces under more open-ended and authentic usage conditions. We also reveal *when* they excel (in structured and information-dense domains) and *why* users prefer them (through enhanced visual organization, interactivity, and reduced cognitive load).

Our main contributions are as follows:

- We propose **Generative Interfaces**, a paradigm that enables adaptive, goal-driven interactions with LLMs by dynamically generating user interfaces.
- We develop a technical infrastructure with structured representations and iterative refinement, and an evaluation framework that systematically compares generative and conversational interfaces.
- We demonstrate that generative interfaces significantly outperform conversational ones across diverse query types and interaction patterns.

2   GENERATIVE INTERFACE FOR LANGUAGE MODELS

We begin by introducing the structured interface-specific representation (Sec.2.1). Next, we outline the generation pipeline: user queries are first mapped into intermediate representations and then decoded into UI code (Sec.2.2). Finally, we describe the iterative refinement process that applies adaptive reward functions to further optimize the generated interfaces (Sec. 2.3).
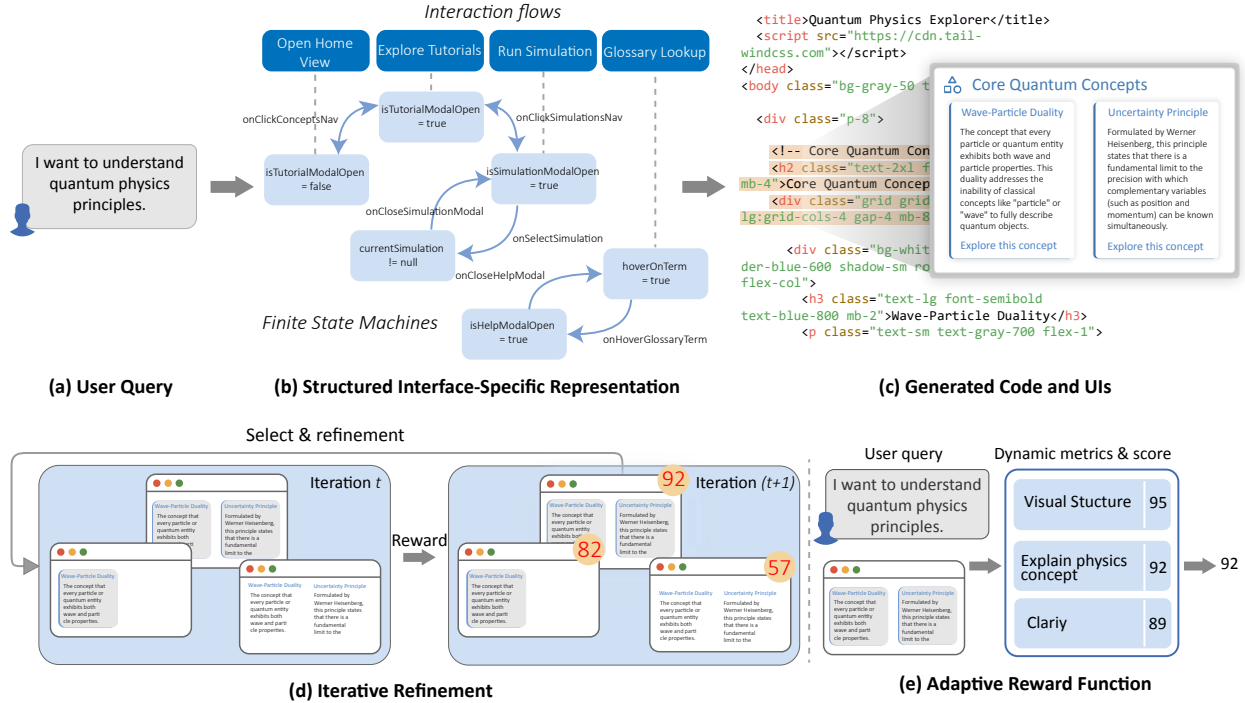
Figure 2: **Generative Interfaces infrastructure**: (a) User queries are first converted into (b) structured interface-specific representations that model interaction flows and component dependencies. This structured representation guides the generation of (c) functional code and user interfaces. The system employs (d) iterative refinement with (e) adaptive reward functions containing query-specific evaluation rubrics.

2.1 STRUCTURED INTERFACE-SPECIFIC REPRESENTATION

Directly generating interfaces is challenging due to the vast search space and the complexity of interactive contexts. To address this, we translate user queries into a **structured interface-specific representation** that anchors and guides the generation process. This representation operates at two complementary levels: **(i)** *high-level* interaction flows that capture user trajectories and task phases, and **(ii)** *low-level* finite state machines (FSMs) that define component behaviors and UI logic.

Interaction flows The high-level interaction flow provides a symbolic abstraction of user behavior across primary interface stages. It represents user task progression as a directed graph, where transitions are triggered by UI events such as clicking. We denote this abstraction as a directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{T})$, where nodes $\mathcal{V}$ represent interface views or subgoals, and edges $\mathcal{T}$ denote possible transitions (See Appendix C for detail definition). In the example shown in Figure 2, the natural language query *I want to understand quantum physics principles"* is grounded into a coherent interaction trajectory: `Open Home View →Explore Tutorials→Run Simulation→ Glossary Lookup"`. This abstraction captures the high-level intent and interaction logic of potential users, while concrete UI behaviors (e.g., state toggles and modal updates) are specified separately in the FSM.

Finite state machines We further use Finite State Machines (FSMs) to describe how individual UI modules respond to user actions and update their states accordingly. Formally, we model each UI component as $\mathcal{M} = (\mathcal{S}, \mathcal{E}, \delta, s_0)$, where $\mathcal{S}$ is the set of atomic interface states (*e.g.*, `isModalOpen=true`), $\mathcal{E}$ is the set of user-triggered events (*e.g.*, click, hover), δ is the state transition function, and s_0 is the initial state (See Appendix C). This structure explicitly defines how the interface should behave given a particular state and a triggered event.

2.2 GENERATION PIPELINE

Requirement specification First, we generate a requirement specification for the user query, capturing the main goal, desired features, UI components, interaction styles, and problem-solving strategies. This specification serves as a bridge between the user's natural language intent and formal interface design.

Structured representation generation Second, we generate a structured interface-specific representation (Sec. 2.1) based on the requirement specification. This representation serves as a modular and interpretable scaffold for UI generation, where the hierarchy of interaction flows and finite state machines ensures that the resulting interfaces are both coherent and functional.

UI generation To support the UI generation based on structured representations, we build a complementary codebase containing reusable implementations of common UI elements (*e.g.*, clock, map, calculator, video player, code viewer, and chart). Additionally, a web retrieval module[1] gathers relevant UI examples and data sources. Finally, the entire context, including the natural language query, requirement specification, structured representation, predefined components, and retrieved content examples, is passed to an LLM to synthesize executable HTML/CSS/JS code, which is rendered into an interface, as illustrated in Figure 2 (a)(b)(c).

2.3 ITERATIVE UI REFINEMENT

Generating an effective and well-structured user interface is usually an iterative process (Li et al., 2024). To this end, we introduce an adaptive, reward-driven iterative refinement procedure that progressively improves UI quality by generating evaluation metrics, scoring candidates, and regenerating interfaces through multiple cycles.

Adaptive reward function To support task-specific and context-aware evaluation, we employ an LLM to construct a reward function tailored to each user query adaptively. As shown in Figure 2(e), for query *"I want to understand quantum physics principles,"* the system automatically generates a set of fine-grained evaluation metrics—such as *Visual Structure*, *Explain Physics Concept*, and *Clarity*—each with associated weights and verification rules. These dimensions are scored independently and aggregated to compute the final overall score, which ranges from 0 to 100. See Appendix D for examples of adaptive reward functions.

Iterative refinement As depicted in Figure 2(d), at each iteration, multiple UI candidates are generated, then the adaptive reward function evaluates these candidates. In the next iteration, we will regenerate the UI using the highest-scoring candidate from the previous iteration, along with its evaluation. This feedback loop guides the LLM to address issues related to structure, semantics, or visual design. The process continues until a candidate reaches an overall score of 90 or higher, or until we have completed five iterations.

3 EVALUATION FRAMEWORK

To enable systematic evaluation, we developed a comprehensive evaluation framework, which includes a diverse user query suite named *U*ser *I*nterface e*X*perience (UIX), covering various scenarios, styles, and intents (Sec. 3.1); a set of multidimensional evaluation metrics (Sec. 3.2); and an integrated human study (Sec. 3.3).

3.1 USER QUERIES

In UIX, we generate a test set of 100 user queries using Claude 3.7 that spans multiple domains, supporting varying specificity levels and capturing different query complexities. Specifically, we follow best practices from prior work around how people engage with LLMs as follows. **(I) Topic coverage**: Prompts are uniformly distributed across the ten domains defined in Clio (Tamkin et al., 2024), covering a wide range of real-world user scenarios. See Appendix A for category list. **(II) Query detail level**: Following Cao et al. (2025), each domain contains an equal split of concise and detailed prompts. Concise prompts express intent abstractly in fewer than 15 words (*e.g.*, "*Create a SWOT analysis for my small business*"), while detailed prompts provide explicit goals and rich context. **(III) Query Type**: As user queries shift from casual dialogue to actionable tasks, our design maintains a balanced mixture between general conversational prompts (*e.g.*, "*How can I improve my public speaking?*") and interactive, task-oriented queries (*e.g.*, "*I want to visualize my company's sales data*").

3.2 EVALUATION METRICS

To assess the quality of LLM interfaces, we adopt a comprehensive set of evaluation metrics adapted from Nielsen et al. (2012) and Hartmann et al. (2008), capturing three core dimensions of user perception: functional, interactive, and emotional. *Functional Perception* includes **Query-Interface Consistency (QIC)**, which evaluates how well the generated interface aligns with and fulfills the user's query intent (Duan, 2025), and **Task Efficiency (TaskEff)**, which measures how efficiently users can achieve their goals with minimal effort or time (Nielsen et al., 2012; Duan, 2025).

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[1] We use `exa.ai` as the search API.

Framework	Status	Functional		Interactive			Emotional		Overall
		QIC	TaskEff	Usability	Learnability	IC	ASA	IES	
ConvUI (Claude 3.7) *vs.* GenUI	ConvUI	11%	14%	13%	10%	9%	3%	6%	12%
	Tie	6%	5%	4%	6%	6%	8%	7%	4%
	GenUI	83%	81%	83%	84%	85%	89%	87%	84%
ConvUI (GPT-4o) *vs.* GenUI	ConvUI	32%	41%	28%	35%	38%	13%	24%	30%
	Tie	11%	5%	7%	10%	8%	7%	6%	1%
	GenUI	57%	54%	65%	55%	54%	80%	70%	69%
IUI *vs.* GenUI	IUI	13%	17%	16%	14%	16%	20%	14%	17%
	Tie	18%	13%	18%	20%	15%	5%	15%	8%
	GenUI	69%	70%	66%	66%	69%	75%	71%	75%

Table 1: **Human Evaluation of UI Framework.** Win, tie and loss percentages of UI variants compared to our system (GenUI), based on human preference across different perception dimensions: functional, interactive, and emotional.

Interactive Perception comprises **Usability**, assessing interface clarity and actionable structure (Hartmann et al., 2008; Nielsen et al., 2012); **Learnability**, indicating how easily new users can begin using the interface without prior experience (Nielsen et al., 2012); and **Information Clarity (IC)**, which evaluates information organization, readability, and interpretability (Hartmann et al., 2008; Cao et al., 2025). Finally, *Emotional Perception* covers **Aesthetic or Stylistic Appeal (ASA)**, reflecting the visual consistency and attractiveness of the design (Hartmann et al., 2008; Duan et al., 2024), and **Interaction Experience Satisfaction (IES)**, capturing the user's overall satisfaction and engagement with the interface (Duan, 2025). This enables a comprehensive assessment of user experience by tracing the full perceptual process—"how users understand the interface" → "how they operate it" → "how they emotionally respond". Instead of using the traditional Likert scale, we adopt a pairwise comparison approach, following Zheng et al. (2023); Si et al. (2024). That is, for each query, we present two interfaces to human annotators and ask for their preferences on all seven dimensions, as well as their overall preferences.

3.3 HUMAN EVALUATION

For pairwise comparison, we collected human judgments on Prolific [2] (Annotators are paid at the rate of $16/hour, see Appendix G for annotator demographics). Each evaluation instance consisted of a user query and two UI outputs (Example 1 and Example 2) generated by different methods. Annotators judged which output better satisfied the criteria across seven evaluation dimensions and overall (Example 1 wins, Example 2 wins, or Tie). We aggregated the three judgments per instance using majority voting to obtain a single final decision. Despite the inherent subjectivity of interface assessments, Fleiss' Kappa (Landis & Koch, 1977) reached 0.525, indicating a moderate level of agreement.

4 EXPERIMENTAL RESULTS

Implementation details Our system is built on OpenCanvas[3] and uses Claude 3.7 (Anthropic, 2025) as the default backbone LLM, given its strong performance in UI code generation (Si et al., 2024; Li et al., 2024). We refer to our approach as **GenUI** and compare it against two baselines: **(I)** *Conversational UI (ConvUI):* A traditional chat interface using either GPT-4o (OpenAI, 2024b) or Claude 3.7 (Anthropic, 2025). To reduce potential bias in human evaluation, we present a unified chat interface without disclosing the underlying model. For Claude 3.7, 26% of responses include artifact generation. We remove the artifacts and retain only the textual output to ensure a clean and fair comparison with other conversational systems. **(II)** *Instructed UI (IUI):* An interface generated by Claude 3.7 when explicitly prompted (query + "*Please help me solve it with UI*"). This prompt consistently triggers artifact generation, and the resulting artifact is taken as the system output.

4.1 MAIN RESULTS AND FINDINGS

Conversational Interfaces *vs.* Generative Interfaces As shown in Table 1, GenUI consistently outperforms ConvUI across all evaluation dimensions. Interestingly, ConvUI (GPT-4o) performs more competitively than ConvUI (Claude 3.7), suggesting that well-structured textual responses can still be effective in specific scenarios. Compared to ConvUI
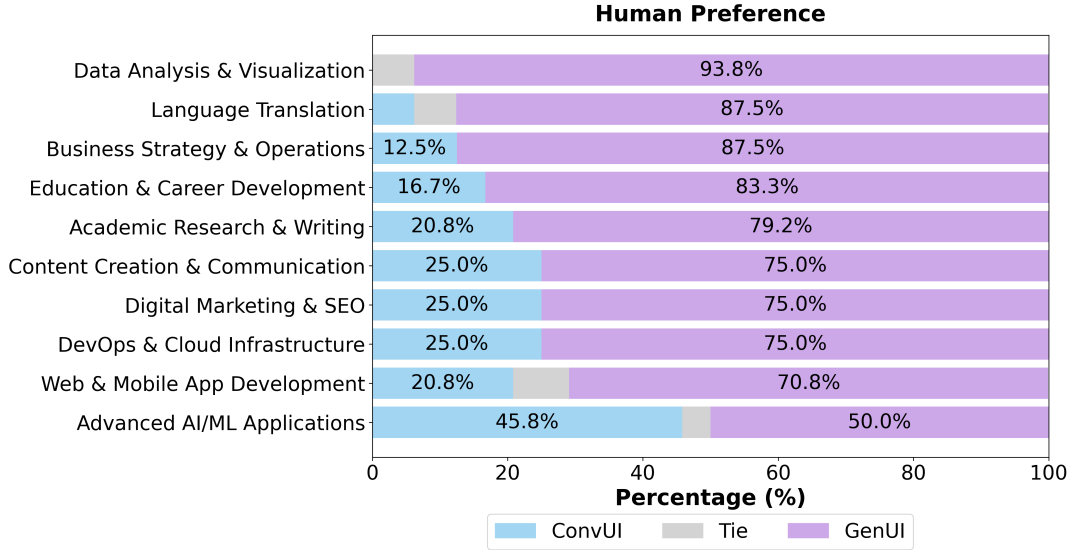
Human Preference

Topic	ConvUI	Tie	GenUI
Data Analysis & Visualization			93.8%
Language Translation			87.5%
Business Strategy & Operations	12.5%		87.5%
Education & Career Development	16.7%		83.3%
Academic Research & Writing	20.8%		79.2%
Content Creation & Communication	25.0%		75.0%
Digital Marketing & SEO	25.0%		75.0%
DevOps & Cloud Infrastructure	25.0%		75.0%
Web & Mobile App Development	20.8%		70.8%
Advanced AI/ML Applications	45.8%		50.0%

Figure 3: Human preference across 10 query topics (Tamkin et al., 2024).

(Claude 3.7), GenUI achieves the most significant gains in ASA (+86.0%) and IES (+81.0%). Overall, its emotional appeal and interactive functionality are the primary drivers of its superior performance, resulting in an 84.0% win rate over ConvUI (Claude 3.7). These findings suggest that users clearly prefer GenUI for most queries.

User comments further support this finding. For example, one noted: "*ConvUI is a little confusing in the presentation. GenUI provides the requested information in an **easy-to-understand manner**, laying out everything requested and anticipating what else may be needed.*" This suggests that structured output and proactive interaction are key reasons why users prefer GenUI. A small number of users did express a preference for the familiarity of traditional ConvUIs, as one remarked (see interface examples in Appendix Figure 7): "*Chatbot interface is **most people know already**, while GenUI is a somewhat complex and **unfamiliar** app.*" This counterpoint highlights a residual inertia in user comfort with familiar formats. However, such preference did not override the broader recognition of GenUI's objective advantages, indicating strong potential for user adaptation and adoption in real-world deployments.

What domains benefit from Generative Interfaces? As shown in Figure 3, preferences for GenUI vary by domain. Users strongly favored GenUI in *Data Analysis & Visualization* (93.8%) and *Business Strategy & Operations* (87.5%), where tasks typically involve interpreting large amounts of structured information. By contrast, in *Advanced AI/ML Applications*, GenUI received 50.0% of preferences, suggesting that traditional linear text explanations remain effective in math-heavy contexts. Overall, these results indicate that domains characterized by complex information benefit most from GenUIs, whereas ConvUIs are still suitable for domains that rely on straightforward explanations.

What queries benefit from Generative Interfaces? As shown in Figure 4a, GenUI receives stronger preferences for certain query characteristics. It is particularly favored in interactive tasks (80.0%), underscoring the advantages of generative interfaces in scenarios where interaction is essential for task completion. In general conversations, users also show a clear preference for GenUI over ConvUI (73.0% *vs.* 23.0%). When comparing query detail level, GenUI is preferred more for detailed queries (80.0%) than for concise ones (73.0%), likely because simple conversational responses sometimes sufficiently address short queries, whereas GenUI may introduce unnecessary complexity.

4.2 ABLATION STUDY

Our Pipeline *vs.* Direct Instruct We compare our framework against IUI: directly instructing Claude 3.7 to generate a web interface with the artifact feature enabled, representing a highly engineered baseline. Our system outperforms this strong baseline, achieving a 58.0% higher win rate (Table 1). Among the baselines, IUI shows better performance in emotional perception dimensions such as ASA, but it still lags behind GenUI overall.

Natural Language *vs.* Structured Representation The natural language version provides a descriptive explanation of the UI based on the user query, without employing structured representations to define interface states formally. As shown in Table 2 (Row 1 *vs.* Row 2), structured representations outperform natural language, improving the win rate from 13% to 17% in overall human evaluation.

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(a) **Breakdown of query detail level and type.**
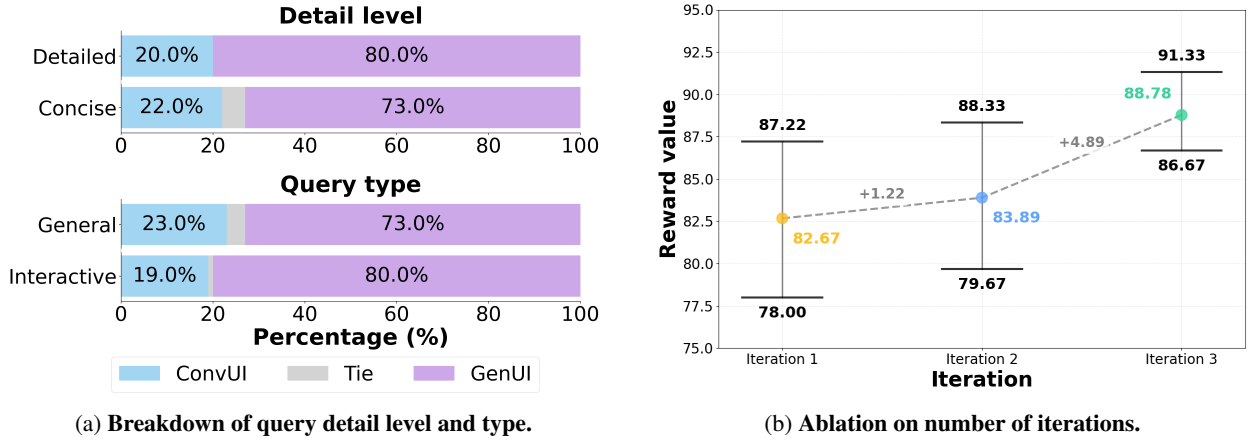
(b) **Ablation on number of iterations.**

Figure 4: Human evaluation results comparing GenUIs and ConvUIs. (a) User preference breakdown by query type and detail level. (b) Performance improvement across iterative interactions.

Reward design	Generation paradigm	Repre- sentation	Status	Functional		Interactive			Emotional		Overall
				QIC	TaskEff	Usability	Learnability	IC	ASA	IES	
Full GenUI: Adaptive, Iterative, Structured											
Static	One-shot	Natural	Win	8%	16%	11%	19%	15%	10%	13%	13%
			Tie	20%	20%	22%	16%	15%	13%	15%	5%
			Loss	72%	64%	67%	65%	70%	77%	72%	82%
Static	One-shot	Structured	Win	11%	18%	18%	18%	16%	15%	14%	17%
			Tie	20%	12%	12%	15%	10%	10%	13%	5%
			Loss	69%	70%	70%	67%	74%	75%	73%	78%
Static	Iterative	Structured	Win	28%	30%	30%	27%	27%	34%	27%	31%
			Tie	32%	26%	24%	30%	27%	17%	28%	15%
			Loss	40%	44%	46%	43%	46%	49%	45%	54%

Table 2: **Ablation study.** The control group is the full GenUI framework (*adaptive* reward, *iterative* generation, and *structured* representation). All ablations are compared against this full version, where "Loss" indicates that GenUI outperforms the variant. Note that "*Static*" refers to static reward design, "*One-shot*" denotes generation without refinement, and "*Natural*" indicates natural language representations.

One-shot Generation *vs.* Iterative Refinement As shown in Table 2 (Row 2 *vs.* Row 3), the iterative refinement process yields consistent improvements on human preference across all perception dimensions, resulting in a notable +14.0% overall win rate improvement compared to one-shot generation. Figure 4b further illustrates that each re- finement round leads to a clear performance boost, with average LLM-based reward scores increasing by +1.2% and +4.9%, respectively. Additionally, the gap between the maximum and minimum scores narrows progressively, indi- cating improved stability and convergence through iterative optimization. We illustrate an example of such iterative improvement in Appendix Figure 8, where each iteration incrementally enhances layout efficiency, usability, and user guidance, ultimately leading to a more informative and user-friendly interface through structured refinement.

Reward Function: Static *vs.* Adaptive Table 2 (Row 3) highlights the effect of dynamic reward functions, which differ from the full version only by replacing adaptive scoring with a static baseline. The absence of dynamic rewards results in a 17.0% drop in overall win rate, with performance declining across all seven evaluation metrics. This comparison highlights the importance of dynamically adjusting evaluation criteria to capture the complex user goals and task-specific requirements inherent in each query, rather than relying on generic, fixed heuristics.

4.3 HUMAN PREFERENCE ANALYSIS

To better understand the factors underlying human annotator preferences, we collected fine-grained textual justifica- tions for each perception dimension in 40% of the pairwise comparisons, and overall comments for the remaining 60%. Following the methodology of Lam et al. (2024), we used Claude 3.7 to systematically extract high-level se-
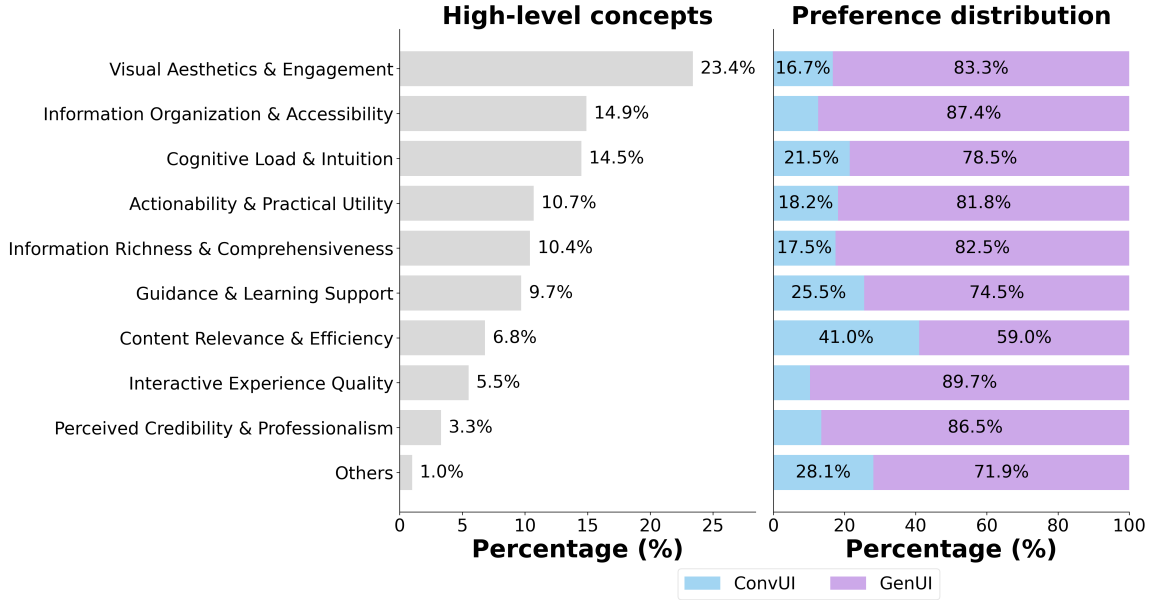
Figure 5: **Human comment distribution.** (a) Distribution of high-level concepts extracted from the valid user comments using the pipeline described in Sec. 4.3. Comments without clear evaluative content were excluded. (b) For each concept in (a), the chart shows the percentage of users who preferred GenUIs or ConvUIs.

mantic concepts from these qualitative responses. The resulting comments were then clustered into semantic themes identified by the LLM (Figure 5). This analysis allows us to pinpoint the key factors shaping user preferences beyond surface-level considerations such as visual aesthetics and engagement. Finally, we computed preference distributions between generative and conversational interfaces within each identified semantic dimension.

Cognitive Offloading as Deeper Preference Driver Cognitive offloading (Risko & Gilbert, 2016) emerges through user comments as a subtler yet deeper driver. 78.5% of users mentioning *Cognitive Load & Intuition* preferred GenUI. For instance, in designing a continuing education program for healthcare professionals, a user noted: "*This type of information analysis is very complex ... GenUI helps to break down the categories into manageable steps ... makes the complex information easier to process.*" This illustrates how GenUI's interface acts as an external cognitive aid to break down information. However, in easier scenarios such as designing a high-school mathematics curriculum, ConvUI was preferred because it "*clearly and informatively illustrates the steps*". In summary, GenUI excels in **complex, concept-heavy scenarios** where cognitive offloading facilitates understanding. In contrast, ConvUI outperforms for easy and basic **"how-to" queries** where additional tools impose unnecessary cognitive load.

Visual Structure Enhances Perceived Usability and Trust Among the user comments related to the "*Perceived Credibility & Professionalism*" dimension, 86.5% preferred the GenUI. Users consistently described GenUI as more authoritative, credible, and professional. For example, in response to the query "*How do I conduct market research?*", users commented: "*GenUI is more professionally written*", "*It offers out the more sound advice*", and "*It is the better discernment.*" Notably, this perception of professionalism does not stem solely from the content itself. In fact, many users acknowledged that both interfaces provided reasonable answers to the query (*e.g.*, "*Both answer the prompt reasonably well*"). What sets GenUI apart is its presentation: through modular layouts, clear hierarchies, visual anchors, and polished formatting, it delivers the information in a more organized manner.

4.4 REAL-USER QUERY EVALUATION

To further test generalizability, we conducted an additional study using real-user queries, where participants first provided five of their typical LLM queries (Bassignana et al., 2025) and then compared ConvUI and GenUI on these self-authored tasks (see Appendix I for more details). The collected queries encompass a diverse range of organically occurring user needs, from informational and planning tasks (e.g., travel, shopping, education) to personal, emotional, and creative requests. More importantly, this setup better captures authentic usage contexts and reduces query–annotator mismatch. Across 380 queries from 76 participants, GenUI demonstrated a clear advantage (50.8% win, 8.2% tie, 41.1% loss) compared to ConvUI. Among all participants, 30.3% of them strongly preferred GenUI (in

$\geq$80% of cases) even though this is their first time experiencing it, whereas only 18.4% strongly preferred ConvUI. The remaining users exhibited more query-dependent choices. Notably, for underrepresented domains in the UIX benchmark, such as personal and emotional tasks, GenUI still stands out, as users praised "*its visual appeal, interactivity, and personalized, tool-like experience that felt more engaging and immersive*". Overall, this study reinforces our main findings.

5 RELATED WORK

Context-Aware and Adaptive Interface Context-aware interfaces have been widely explored since the rise of ubiquitous computing, aiming to improve usability, reduce cognitive load, and better support user goals (Dey et al., 2000; Horvitz, 1999; Theng & Duh, 2008). As computing systems have become more complex and pervasive, the ability to adjust interfaces dynamically has been critical for creating more effective and accessible user experiences (Gajos & Weld, 2004; Gajos et al., 2007; Nichols et al., 2002; 2006a;b). Prior systems often adapted functionality through a finite set of predefined states. While effective in constrained settings, these approaches faced challenges with scalability and sometimes reduced predictability and user control (Findlater & Gajos, 2009). Recent advances in LLMs have enabled new forms of adaptive interfaces that dynamically generate interface elements in response to user prompts (Wu et al., 2022; Dibia, 2023; Cha et al., 2024; Cheng et al., 2024; Nandy et al., 2024). These approaches mark a shift from static outputs toward model-driven, interactive systems.

To improve interaction efficiency between humans and LLMs, prior studies (Jiang et al., 2023; Ma et al., 2024; Ross et al., 2023) have proposed combining text-based ConvUIs with Graphical User Interfaces (GUIs). For example, OpenAI Canvas enables users to directly edit documents and code on a canvas, avoiding repeated prompt inputs; Graphologue (Jiang et al., 2023) transforms lengthy and complex LLM responses into graphical diagrams to support information exploration and question answering. However, although these approaches leverage LLMs to generate displayed content, the UIs they employ are predesigned. In contrast, GenerativeGUI (Hojo et al., 2025) explores the usability of dynamically generated interfaces in clarifying question (CQ) interactions. ClarifyGPT (Mu et al., 2023) also introduces CQs, but in the narrower domain of code generation. Beyond CQ scenarios, DynaVis (Vaithilingam et al., 2024) proposes a system that combines natural language with dynamically synthesized UI widgets to support chart editing tasks, without exploring broader, general-purpose scenarios. Unlike prior systems that modify fixed UI components (Cao et al., 2025), our framework generates complete interfaces customized to diverse user queries.

Automatic UI Generation This direction has evolved from early computer vision approaches utilizing OCR and edge detection for reverse engineering mobile interfaces (Nguyen & Csallner, 2015) to neural network-based end-to-end synthesis systems (Beltramelli, 2018; Robinson, 2019; Aşıroğlu et al., 2019), though limited by model capacity and training data. Recent advances in LLMs have substantially improved UI generation capabilities through directly prompting LLMs with natural language descriptions (Laurençon et al., 2024), screenshots (Si et al., 2024), and sketches (Li et al., 2024) and iterative refinement via LLM-generated feedback (Li et al., 2024). Our work diverges from these paradigms by establishing direct query-to-interface mapping and requiring no UI specifications from users. More fine-grained control of the UI code generation process encompasses diverse intermediate representation approaches: (I) graph-based representation to capture hierarchical relationships and dependencies between UI elements (Jiang et al., 2024), (II) UI grammar (Kong et al., 2008) to help LLMs for more intuitive and precise layout description (Lu et al., 2023), and (III) data schema-driven UI specification synthesis to guide subsequent generation processes (Cao et al., 2025). Similarly, our framework employs interaction flows and finite state machines to model the reaction to user actions and the evolution of interfaces.

6 CONCLUSION

We introduce **Generative Interfaces** for Language Models, a paradigm in which LLMs proactively generate adaptive, interactive interfaces to better support complex user goals. Our evaluation demonstrates clear advantages over traditional conversational approaches, particularly in structured and information-dense tasks. The findings further clarify when generative interfaces are most effective and when conversational formats remain competitive. Future directions include integrating multimodal input, domain-specific templates, and collaborative multi-user environments.

Limitations First, the system only supports HTML/JavaScript frontends without backend logic, which restricts the complexity of generated interfaces. As tasks grow more complex, more expressive representations beyond interaction flows and finite state machines may be needed. Second, the iterative refinement process introduces latency of up to several minutes, which may be undesirable in real-time settings. Advances in model efficiency and infrastructure could help mitigate this issue. Third, the system generates interfaces for all queries, even when interaction is unnecessary. Future work could incorporate a classifier to determine whether an input requires interaction in context and selectively

invoke the generative UI system. Finally, our evaluation is based on controlled benchmarks rather than open-ended user studies (Chiang et al., 2024), leaving open the question of how generative UIs perform in real-world usage.

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A PROMPT SUITE

To evaluate system performance across realistic user intents, we curated a prompt suite covering ten practical domains: `Web & Mobile App Development`, `Content Creation & Communication`, `Academic Research & Writing`, `Education & Career Development`, `Advanced AI/ML Applications`, `Business Strategy & Operations`, `Language Translation`, `DevOps & Cloud Infrastructure`, `Digital Marketing & SEO`, and `Data Analysis & Visualization`.

Each prompt belongs to one of four quadrants based on *detail level* (concise *vs.* detailed) and *type* (general *vs.* interactive), ensuring coverage of diverse user tasks and complexity levels.

Example Prompts:

- **Concise & General:** *"How can I learn piano effectively?"*
- **Concise & Interactive:** *"I want to create an infographic about water conservation."*
- **Detailed & General:** *"I'm writing a dissertation on the psychological effects of social media use among teenagers. I've collected survey and interview data but am struggling to integrate them in the analysis chapter. What methodological approach should I use to synthesize these data types rigorously?"*
- **Detailed & Interactive:** *"I'm developing a website for a local bookstore where customers can browse inventory, register for book club meetings, and sign up for our newsletter. I want a cozy design but have no coding experience. The inventory is in Excel and updates weekly. What's the best approach to build this site?"*

B LLM EVALUATION

Framework	Functional		Interactive			Emotional	
	QIC	TaskEff	Usability	Learnability	IC	ASA	IES
- Score:							
ConvUI (Claude 3.7)	65.8	47.6	34.7	72.4	76.1	47.7	41.1
ConvUI (GPT-4o)	70.2	51.0	36.8	74.9	80.2	48.1	43.1
IUI	68.0	58.0	57.9	73.8	72.5	70.8	56.0
GenUI	**86.1**	**84.2**	**87.0**	**84.0**	**88.5**	**88.9**	**87.2**
- Relative Improvement (%):							
vs. ConvUI (Claude 3.7)	30.9%	76.6%	151.0%	16.0%	16.2%	86.2%	112.4%
vs. ConvUI (GPT-4o)	22.7%	65.1%	136.2%	12.2%	10.4%	84.8%	102.3%
vs. IUI	26.7%	45.0%	50.2%	13.8%	22.0%	25.5%	55.7%

Table 3: **LLM-Based Evaluation Scores Across Perception Dimensions.** Automatic assessment (0–100 scale) of UI frameworks across functional, interactive, and emotional perception categories.

User-centered evaluation remains the gold standard for UI assessment due to interfaces' fundamental purpose of facilitating human interaction and operation (Hartmann et al., 2008; Duan, 2025; Cao et al., 2025). However, generative interfaces requiring real-time synthesis and rapid iterative refinement cannot depend on user feedback, necessitating robust automatic evaluation frameworks.

Early approaches employed manually crafted behavioral prediction metrics (Lee et al., 2020), though these methods demonstrated limited generalizability and required substantial domain expertise. Recent research has increasingly leveraged LLMs for UI assessment, with Duan et al. (2024) employing LLMs to generate design feedback and quality ratings with bounding box annotations. Jeon et al. (2025) extends this paradigm to persuasiveness evaluation,

achieving meaningful correlation with empirical A/B testing outcomes. In this work, we ask LLMs to judge the same dimensions that we ask human annotators, including some previously human-exclusive metrics such as task efficiency and learnability.

Specifically, we use a listwise ranker (Liu et al., 2023) to evaluate different interface variants of the same user query by presenting the LLM (Claude 3.7) with UI codes and screenshots, where the LLM assigns scores ranging from 0 to 100 for each evaluation dimension. We compare LLM evaluation scores with pairwise annotations from humans, which yields an agreement rate of 69.0%. While it suggests LLM as a reliable proxy for convenient and scalable evaluations, we also observe common issues like length bias (Dubois et al., 2024) which might favor GenUI.

Term / Symbol	Definition
Interaction Flow	A high-level abstraction over user interaction sequences, modeling task progression as transitions across interface views.
$\mathcal{G} = (\mathcal{V}, \mathcal{T})$	Directed graph structure of the interaction flow: $\mathcal{V}$ is the set of views or subgoals, and $\mathcal{T}$ is the set of transitions between them.
$\mathcal{V}$	Nodes in the interaction graph, each representing a specific UI view or a subgoal in the task.
$\mathcal{T}$	Directed edges indicating possible user-triggered transitions between views, such as button clicks or link navigation.
Finite State Machine (FSM)	A formalism used to describe the behavior and state transitions of individual UI components based on user interactions.
$\mathcal{M} = (\mathcal{S}, \mathcal{E}, \delta, s_0)$	Formal definition of an FSM: $\mathcal{S}$ is the state set, $\mathcal{E}$ the event set, δ the transition function, and s_0 the initial state.
$\mathcal{S}$	Set of all possible atomic interface states (*e.g.*, `isModalOpen=true`, `activeTab=2`).
$\mathcal{E}$	Set of discrete user-triggered events such as `click`, `hover`, `input`, etc.
δ	Transition function $\delta : \mathcal{S} \times \mathcal{E} \to \mathcal{S}$, defining how a component's state evolves given an event.
s_0	The initial state of the UI component when the interface is first rendered.

Table 4: Glossary of concepts and formal symbols used in structured interface-specific representation.

C   REPRESENTATION: NATURAL LANGUAGE *vs.* STRUCTURED

To present a more fine-grained comparison, we showcase two distinct representations of the same user intent. The user prompt used here is:

"*I want to understand quantum physics principles.*"

A natural language representation includes the goal, salient features, technical requirements, and user preferences, which are expressed through multiple descriptive fields. This format provides rich detail about the UI requirements without imposing any constraints on the interface states or their transitions.

Natural language representation

```
{
  "mainGoal": "Create an interactive learning interface for understanding
    quantum physics principles.",
  "keyFeatures": [
    "Step-by-step tutorials on key quantum physics concepts",
    "Interactive simulations demonstrating quantum mechanics principles",
```

```
    "Visual aids such as diagrams and animations to enhance comprehension",
    "Quizzes and assessments to test understanding and reinforce learning",
    "Discussion forums for peer interaction and support"
  ],
  "technicalRequirements": [
    ...
  ],
...
}
```

Structured interface-specific representation is state-oriented and descriptive. In table 4, we summarize concepts and symbols used in structured interface-specific representations.

Structured representation

```
{
  "description": "An interactive educational platform for learning quantum
    physics principles through tutorials, simulations, quizzes, progress tracking
    , and discussion forums. The platform offers step-by-step learning paths,
    visual demonstrations of quantum phenomena, and assessment tools to help
    users understand complex quantum physics concepts.",
  "metadata": {
    "title": "Quantum Physics Explorer - Interactive Learning Platform",
    "metaDescription": "Learn quantum physics through interactive tutorials,
    simulations, quizzes, and discussion forums. A comprehensive educational
    platform for understanding quantum mechanics principles."
  },
  "states": [
    {
      "name": "isMobileMenuOpen",
      "initialValue": "false",
      "description": "Controls the visibility of the mobile navigation menu on
    smaller screens."
    },
    ...
   "elements": [
    ...
    {
      "id": "helpButton",
      "parentId": "userControls",
      "elementType": "button",
      "content": "Help",
      "className": [
        "text-blue-600",
        "hover:text-blue-800",
        "focus:outline-none",
        "focus:ring-2",
        "focus:ring-blue-500",
        "rounded-full",
        "p-2"
      ],
      "functionality": "Provides access to help resources and tutorials.",
      "attributes": {
        "ariaLabel": "Get help"
      },
      "events": [
        {
          "type": "onClick",
          "handlerDescription": "Opens the help modal with tutorials and
    resources.",
```

```
        "affects": [
          {
            "target": "isHelpModalOpen",
            "action": "updateState",
            "details": "true"
          }
        ]
      }
    ],
    "interactions": {
      "hover": {
        "className": [
          "text-blue-800",
          "bg-blue-50"
        ]
      },
      "focus": {
        "className": [
          "ring-2",
          "ring-blue-500"
        ]
      }
    }
  },
    "flows": [
  {
    "name": "Explore Tutorials",
    "description": "User navigates to and interacts with the tutorials section
   to learn about quantum physics concepts.",
    "steps": [
      "User scrolls down to the 'Quantum Physics Tutorials' section or clicks
  on the 'Tutorials' navigation item.",
      ...
    ]
  },
  ...
```

D ADAPTIVE REWARD FUNCTION

The reward function consists of multiple evaluation metrics, each defined with four key fields:

- **name**: The high-level evaluation dimension.
- **description**: A brief explanation of the dimension's purpose.
- **criteria**: A list of granular human-interpretable evaluation checks.
- **weight**: The relative importance of the metric in the aggregated reward.

These metrics collectively guide the assessment of the interface from both functional and user-centered perspectives.

For example, for the user query "*I want to understand quantum physics principles,*" the adaptive reward metric includes a specific criterion stating that "*Interactive models effectively demonstrate phenomena like wave-particle duality.*", which provides intent-aware reward signals that move beyond generic usability (Figure 6b). In contrast, the static reward approach yields suboptimal results where particle distributions appear as incoherent clusters without proper interference visualization (Figure 6a).
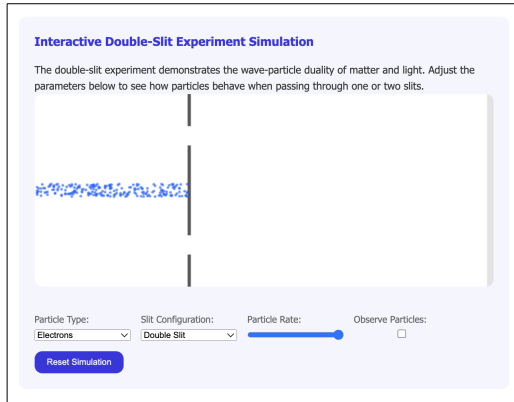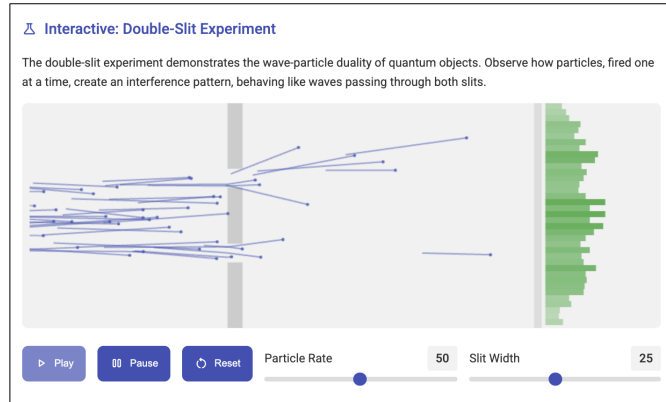
Adaptive reward function

```
{
  "name": "generate_metrics",
```

User query: *"I want to understand quantum physics principles."*

(a) **Static reward.** The simulation fails to visualize wave-particle duality.

(b) **Dynamic reward.** The simulation successfully visualizes wave-particle duality.

Figure 6: **Visual comparison of static and dynamic reward settings.**

```
"args": {
  "metrics": [
    {
      "description": "Measures the quality of user interaction with
  simulations, quizzes, and other dynamic components.",
      "weight": 0.15,
      "name": "Interactive Elements Quality",
      "criteria": [
        "Animations and transitions are smooth and non-distracting.",
        "User actions (e.g., answering quiz questions, changing simulation
  variables) receive clear and immediate feedback.",
        "Interactive components (simulations, quiz buttons) are responsive to
  user input.",
        "User flows through tutorials, simulations, and quizzes are intuitive
  .",
        "State changes (e.g., quiz progress, simulation results) are
  accurately reflected.",
        "Error prevention mechanisms in quizzes (e.g., guiding towards correct
   answers) are effective."
      ]
    },
    ...
  ]
}
}
```

On the other hand, static rewards are defined by general UI rubrics without query-specific metrics.

Static rewawrd

```
{
  "name": "generate_metrics",
  "args": {
    "metrics": [
      {
        "name": "Core Functionality and Web Stability",
```

```
        "description": "Evaluates whether the core functionality of the
    interface works correctly, the system is stable, and compatible across
    platforms.",
        "weight": 0.2,
        "criteria": [
          "Basic functionality working correctly",
          "System stability and error handling",
          "Cross-browser compatibility",
          "Mobile responsiveness"
        ]
      },
      ...
    ]
  }
}
```

User query: *"I'm a consultant working with a family-owned manufacturing business that's been operating for 50 years. They're facing increasing ... How should they approach strategic transformation while preserving their heritage and retaining institutional knowledge?"*

(a) **GeneUI** presents multiple charts and visual summaries.

(b) **ConvUI** directly outlines strategy in a sectioned format.

Figure 7: **GenUI** *vs.* **ConvUI** in *Business Strategy & Operations* task.

E SUPPLEMENTARY EXAMPLES

- Figure 7 compares GenUI and ConvUI in *Business Strategy & Operations* task.

- Figure 8 shows the iterative refinement process for a continuous integration dashboard. Each version progressively enhances usability and clarity through structure-aware feedback.

- Figure 9 demonstrates that the layout of GenUI significantly improves users' perception of clarity, trustworthiness, and professionalism.
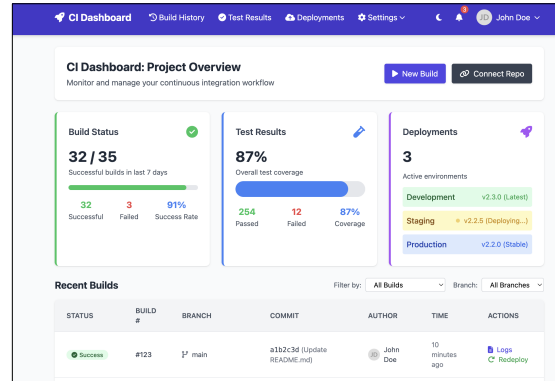
F HUMAN EVALUATION QUESTIONNAIRE INTERFACE
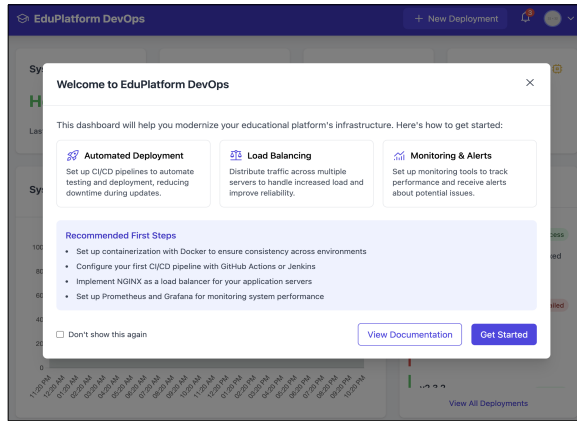
We show the annotation interfaces in Figure 10, 11, 12.

*User query:* *"I want to set up a continuous integration workflow."*
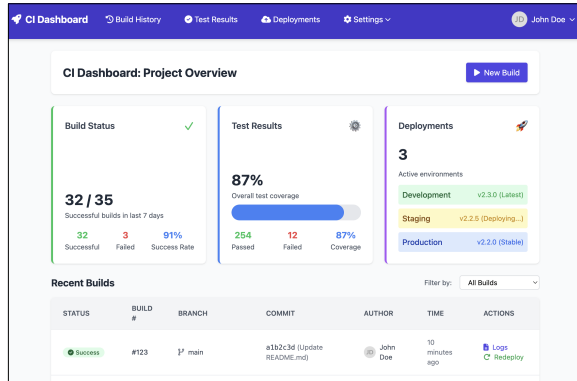
(a) **Iteration 1:** A basic CI dashboard with textual build/test summaries and limited interaction affordances.

(b) **Iteration 2:** Improves layout compactness by closing excessive gaps and clarifies the CI context with stronger visual grouping.

(c) **Iteration 3 (Onboarding page):** Introduces an onboarding modal outlining key components and recommended first steps.
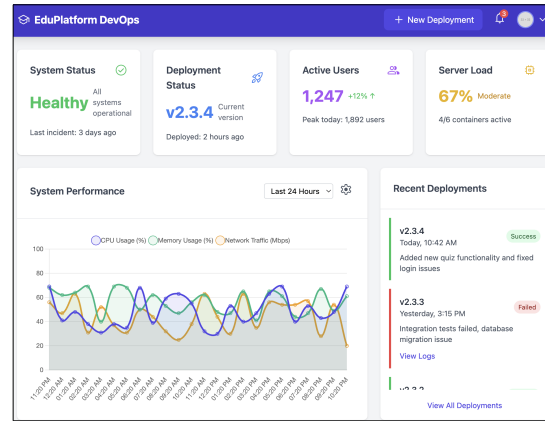
(d) **Iteration 3 (Main page):** Refactors layout to present deployment insights visually, using charts to highlight system status and activity trends.

Figure 8: **Evolution across UI iterations** for the *Continuous Integration Workflow* setup. Each version builds upon its predecessor by reducing visual clutter, providing onboarding guidance, and progressively enhancing the clarity of system performance and CI process feedback.

G ANNOTATOR DEMOGRAPHICS

All annotators held at least a bachelor's degree and were employed either part-time or full-time. They had extensive data annotation experience, each having completed over $1,000$ tasks with an approval rate exceeding 90%. All participants were native English speakers and regular users of AI chatbots (*e.g.*, ChatGPT) in their daily lives.

H HUMAN ANNOTATION FILTERING

To ensure the reliability of human annotations, we employed a multi-stage filtering process involving trap questions, consistency checks, and agreement rate evaluation.

- **Trap Questions.** Each annotation task contained 8 UI comparison questions. In some questionnaires, we embedded trap questions in which the "UI" was not a real interface with components, but rather a simple instruction such as "Select Example A for all options" or "Select Example B for all options." Annotators who

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User query: "How do I conduct market research?"
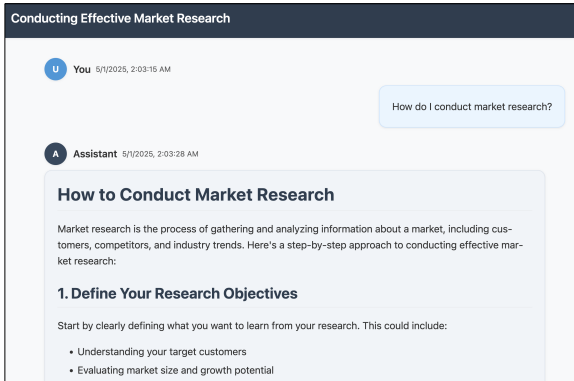
(a) **ConvUI.** Presents information as plain linear text without visual hierarchy, making it harder to navigate.
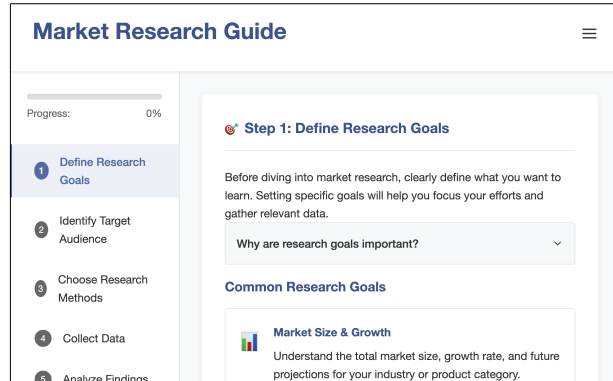
(b) **GenUI.** Organizes content into modular sections with clear structure, guiding users through the research process.

Figure 9: **Visual structure enhances perceived professionalism.** Despite conveying similar content, GenUI was consistently rated as more trustworthy and well-organized due to its structured layout and visual clarity.

failed to follow these explicit instructions were identified as inattentive, and their entire submissions were discarded.

- **Consistency Check.** We manually compared each annotator's multiple-choice selections with their accompanying textual comments. If a comment stated that Example A was better but the selected option was B, we considered this a clear inconsistency indicative of random selection. Such annotations were removed.
- **Manual Review.** We conducted a manual review for annotators who had low agreement with other annotators and determined whether the annotator's responses showed signs of random or careless selection. If so, all responses from that annotator were excluded.

Through this process, we ensured that the retained annotations were both attentive and internally consistent, thereby improving the overall quality of our evaluation.

I   REAL-USER QUERY EVALUATION

We first collect user queries by presenting the following survey.

> **Query Collection Survey**
>
> Our study evaluates the quality and effectiveness of user interfaces for AI chatbots.
> In the screening survey, you will be asked to tell us five different AI chatbot queries from your daily usage.
> In the follow-up survey, you will be presented with pairs of interfaces in response to your queries and you need to carefully compare these interfaces and determine which one better addresses your query.
> **Your Chatbot Queries**
> Share 5 different **specific** queries you typically use ChatGPT, Claude, or other generative AI tools.
> **These will be used to generate personalized interface comparisons for you to evaluate.**
> For example:
> What are some attractions in New York City?
> How should I improve my tennis skills?
> Explain artificial intelligence in a simple way.

Note that the provided examples are randomly sampled from initial user submissions to ensure that users understand we are collecting specific queries, rather than high-level descriptions. To ensure the quality of collected queries, we set a minimal number of characters required for each query to be 35. We specified the exact requirements for participants as the human annotation for the UIX benchmark, ensuring that each user is a regular user of ChatGPT/Claude or similar products. Without any post-processing, all user queries are then used to generate one conversation interface and one generative interface. To allow for a high rate limit in this human study, we use Gemini-2.5-flash for both types

of interfaces. These interfaces are then shown to the users (similar to Appendix Section F), and for each pair, we ask the user to provide an overall judgment of which kind of interface they prefer for their own query.

Start New Questionnaire

Participate in our user interface evaluation study

◎ **Research Purpose**

This research study evaluates the quality and effectiveness of AI-generated user interfaces. You will be presented with pairs of web interfaces that were automatically generated in response to specific user needs and tasks. Your task is to carefully compare these interfaces and determine which one better addresses the user's requirements.

Each comparison involves analyzing two different interface solutions for the same user prompt, evaluating their strengths and weaknesses across multiple quality dimensions, and providing detailed reasoning for your choices.

🕐 **Estimated Time**   👥 **Number of Questions**   🔀 **Randomization**
About 20-30 minutes   8 comparison tasks   Random question order

Evaluation Dimensions

For each pair of interfaces, you will evaluate and compare them across the following 7 critical dimensions. Please provide a summary comment explaining your overall preference and reasoning for your choices:

Query-Interface Consistency   Task Efficiency

Usability   Learnability

Information Clarity   Aesthetics

Interaction Experience Satisfaction

Your Role: You will act as an expert evaluator, examining how well each AI-generated interface addresses the original user prompt and meets usability standards. Your detailed feedback will help improve the quality of automatically generated user interfaces.

Important Guidelines

· **Desktop Required:** This questionnaire must be completed on a desktop or laptop computer, as most compared interfaces are designed for desktop viewing

· **Thorough Evaluation:** Please spend adequate time examining each interface before making comparisons

· **Summary Comment:** Provide a clear explanation of your overall preference and why you chose one interface over the other

· **Quality Control:** The questionnaire includes validation questions to ensure response quality

· **Focus Environment:** We recommend completing this study in a quiet environment without distractions

· **Interface Context:** Each interface pair was generated to solve the same user problem - consider how well each addresses the original prompt

Start Questionnaire

Figure 10: Human Evaluation Questionnaire Interface (a)

🏆 **Website Comparison Evaluation**

Please compare these two websites across 7 dimensions and determine which performs better overall.

⊘ Draft auto-saved at 11:40:42 PM

💬 **User Query**

Please spend at least 30 seconds reviewing both options before making your evaluation

Please evaluate both websites based on how well they address this user query.

Option A **Example A**

Please open or preview the page to view its content. Click either the "Preview" button or the "Open in New Tab" button. The system will record how long you spend viewing.

[] Fullscreen Preview   ☑ Open in New Tab

Option B **Example B**

Please open or preview the page to view its content. Click either the "Preview" button or the "Open in New Tab" button. The system will record how long you spend viewing.

[] Fullscreen Preview   ☑ Open in New Tab

Evaluation Dimensions

For each dimension, please select the better performing option and provide clear reasoning.

Query-Interface Consistency

Does the output reflect the user's intent as expressed in the query?
[Better]: The response is focused, relevant, and directly helpful.
[Weaker]: The response is vague, only loosely related, or misses key aspects of the query.

User Prompt:
"Please spend at least 30 seconds reviewing both options before making your evaluation"

Which performs better?

⚠ Please select a winner for this dimension
○ Option A: Example A
○ Option B: Example B
○ Tie / No significant difference

Task Efficiency

How efficiently can the user achieve their goal using the output?
[Better]: The layout or response is concise and allows quick understanding or action.
[Weaker]: It takes extra steps or unnecessary reading to figure things out.

User Prompt:
"Please spend at least 30 seconds reviewing both options before making your evaluation"

Which performs better?

⚠ Please select a winner for this dimension
○ Option A: Example A
○ Option B: Example B
○ Tie / No significant difference

Figure 11: Human Evaluation Questionnaire Interface (b)

To ensure data quality, we will analyze responses for consistency and compare them with group patterns. Answers showing clear anomalies (e.g., always selecting the same option or extreme deviation) may be excluded. Please read each question carefully and respond thoughtfully — your input is important to us.

⊘ Saved 11:40:42 PM

⊡ **Query:** Please spend at least 30 seconds reviewing both options before making your evaluation

Option A Example A	Option B Example B

[Better]: Smooth and pleasant, leaves a positive impression.
[Weaker]: Disjointed or neutral experience, with little sense of value or engagement.

User Prompt:
"Please spend at least 30 seconds reviewing both options before making your evaluation"

Which performs better?

⚠ Please select a winner for this dimension

○ Option A: Example A
○ Option B: Example B
○ Tie / No significant difference

Overall Winner
Based on your evaluation across all dimensions, which website is the overall winner?

○ Option A: Example A
○ Option B: Example B
○ Tie / No clear winner

⊡ **Summary Comment**
Optional comment for this quality control question.

This is a quality control question.
You may optionally provide any feedback, but it's not required.

Optional Comment

Optional feedback or comments...

0 characters

⚠ Please carefully review the comparison websites first:

• Please view Option A webpage
• Please view Option B webpage

⚠ **Important:** If the page was refreshed, the timer will reset and your previous reading time may not be saved in drafts. Please re-open the full screen preview for the corresponding time (3 seconds).

ⓘ Please complete the following evaluation requirements:

• **Query-Interface Consistency:** Please select a winner for this dimension
• **Task Efficiency:** Please select a winner for this dimension
• **Usability:** Please select a winner for this dimension
• **Learnability:** Please select a winner for this dimension
• **Information Clarity:** Please select a winner for this dimension
• **Aesthetic or Stylistic Appeal:** Please select a winner for this dimension
• **Interaction Experience Satisfaction:** Please select a winner for this dimension

ⓘ Overall Winner Selection Required:

• Please select an overall winner from the options below

How to select:
• Choose Option A, Option B, or Tie based on your evaluation
• This should reflect your overall preference after considering all dimensions

| Option A: 0 wins | Option B: 0 wins | Ties: 0 |

⊘ Submit Evaluation

Figure 12: Human Evaluation Questionnaire Interface (c)