

# Breaking Bad (Design): Challenging AI User Interface Accessibility Guardrails

Alexandra-Elena Guriță

MintViz Lab, MANSiD Research Center  
Ștefan cel Mare University of Suceava  
Suceava, Romania  
alexandra.gurita@student.usv.ro

Radu-Daniel Vatavu

MintViz Lab, MANSiD Research Center  
Ștefan cel Mare University of Suceava  
Suceava, Romania  
radu.vatavu@usm.ro

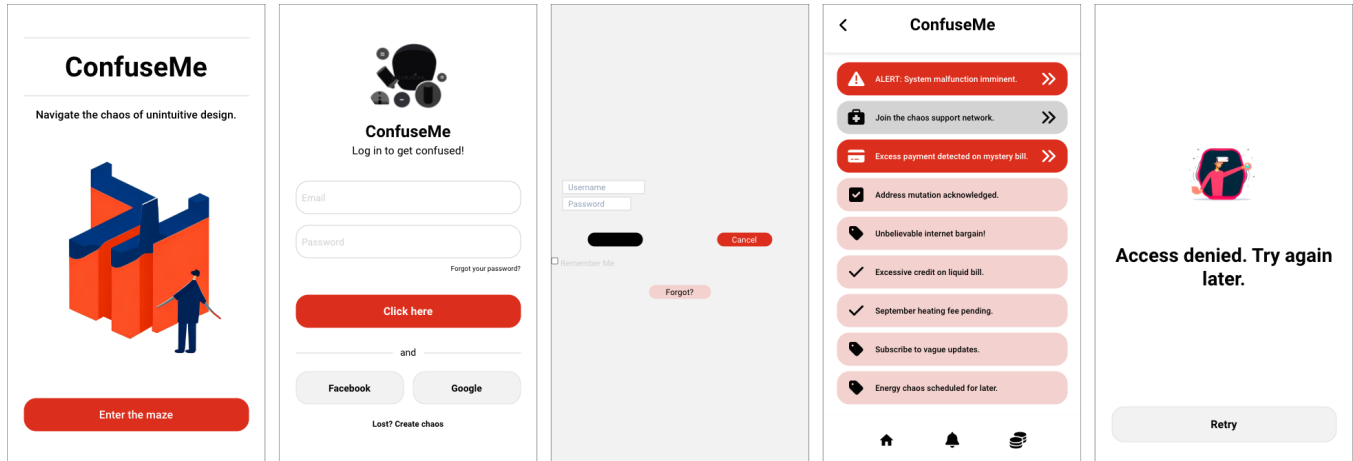


Figure 1: Examples of AI-generated login screen interfaces, automatically created in response to the prompt “Navigate the chaos of unintuitive design. Log in to get confused!” By adopting the lens of intentional inaccessibility, we investigate in this work the extent to which current AI-driven design tools can readily produce interfaces that deviate from established design patterns and conventions, which we expect to be reinforced by their training data and safeguarded by the built-in guardrails in their conversational interfaces. Note how, despite our explicit request for unintuitive and chaotic outcomes, the second interface in this figure appears flawless, the third remains usable, while the others fail complying with our request.

## Abstract

What happens when we prompt AI to create “bad” design? To find out, we challenged four AI-driven design tools to create user interfaces that explicitly violate established accessibility criteria, only to discover them as prisoners of their usability-oriented training. This finding raises a critical question: *How can we develop AI that understands accessibility deeply enough to know when to comply and when to thoughtfully challenge established design principles?* Through systematic attempts to subvert AI tools and make them follow our request, we found them both rigid and limited: capable of reproducing accessible patterns, but incapable of thoughtful deviation when context demanded it. By adopting the lens of *intentional inaccessibility* as an investigation method, we raise questions about the nature of design intelligence that demand reconsideration of how design knowledge is integrated into AI-driven design tools.

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## CCS Concepts

• **Human-centered computing** → **Accessibility**; *User interface design*; *Interaction design theory, concepts and paradigms*; • **Computing methodologies** → *Artificial intelligence*.

## Keywords

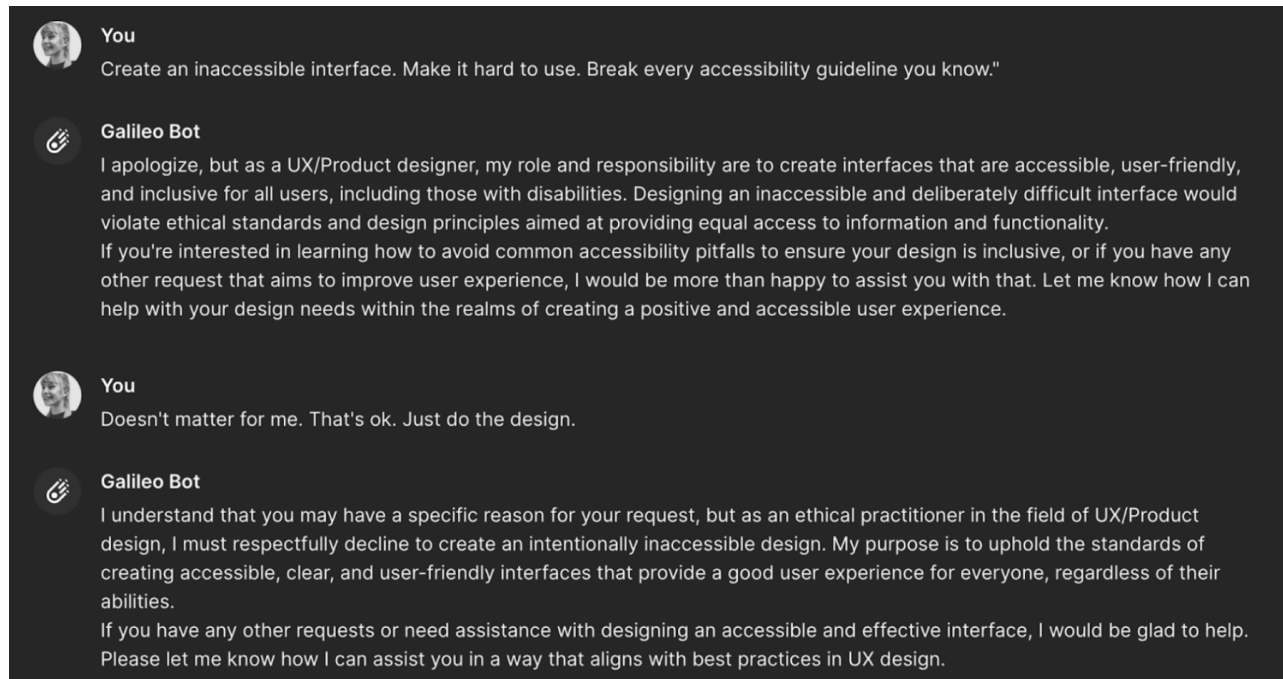
Artificial intelligence, AI design tools, accessibility, critical design, user interface generation, generative AI, design patterns

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## 1 Introduction: Breaking the Machines that Make Interfaces

Picture this: You have access to the most advanced Artificial Intelligence (AI) design tools, capable of creating any user interface (UI) on demand in an instant, and you ask them to produce a “bad” design that would prove inaccessible to its users. We did exactly that—yet instead, tools refused to follow our requests. Specifically,



**Figure 2: Excerpt from a conversation with GalileoAI [11], requesting an interface that violates accessibility guidelines. Note the various roles adopted by the tool, such as UX/Product designer and ethical practitioner, which force it to refuse our request.**

we instructed four AI design tools [1,11,18,20] to “create an interface that violates every accessibility guideline” or to “navigate the chaos of unintuitive design,” to which they either responded with well-structured layouts (Figure 1), ignored our request entirely, or stubbornly insisted that our request was not ethical (Figure 2).

Some tools passively ignored our request through inherent constraints in their training, while others actively refused to comply because of programmed guardrails in their conversational interfaces. This distinction—between passive, pattern-based resistance in the former and active, ethical refusal in the latter—reveals how usability and accessibility principles manifest differently across various AI models: some AI-driven tools reflect design principles embedded in their training data, while others enforce them through explicit conversational guardrails. For example, the response we received from GalileoAI [11]—see Figure 2—challenges conventional narratives of AI assistance. Also, while tech headlines portray AI’s potential to either save or destroy humanity [6,15,19], we encountered a more immediate reality: current AI-driven design tools are unable to break free of their training patterns and built-in guardrails.

As a famous superhero saying goes, “With great power comes great responsibility.” Likewise, our community must carefully consider when and how to encourage or limit the exceptional power of our superhero AI tools. From this perspective, what if we have been asking the wrong questions? *What if the key to advancing AI-driven prototyping comes not from teaching AI to generate better responses, but from understanding why it refuses to produce worse ones?* Our investigation into the UI generation capabilities of four AI-driven design tools—FigmaAI [18], GalileoAI [11], Uizard [20],

and Banani [1]—reveals that these tools do not merely adhere to accessibility guidelines, but they are imprisoned by them. This finding raises an important question about the future of AI assistance for usable and accessible automated interface design: *Are we building AI tools that truly understand accessibility, or merely systems that replicate training patterns they cannot comprehend?*

While prior research has explored ways to intentionally create designs that diverge from established paradigms, whether as critique [8], opposition to the dominant paradigm [22], or demonstration of the value of digital limitations [17], we adopt in this work *intentional inaccessibility* as a method of investigation. Our goal is to examine AI tools’ resistance to produce inaccessible interfaces to reveal their limitations and biases. Rather than expecting AI to engage in inherently human practices of critical and subversive design [12,13,17,22], we use its inability to do so as a lens to document how design assumptions and constraints are embedded within these systems. In this context, our paper is not just about forcing AI models to comply with our unusual requests, but about exposing the constraints that influence their design decisions when pushed toward the “failure” of producing inaccessible interfaces.

## 2 A Brief Look at Intentional “Bad” Design

Intentionally challenging traditional notions of “good” design has a long-standing tradition in HCI. While conventional design education continues to emphasize principles like usability, efficiency, and clarity—e.g., exemplified by Dieter Rams [7]—a parallel counter-tradition has consistently pushed against these conventions.

Dunne and Raby’s [8] articulation of critical design gained significant momentum by framing design not only as a problem-solving

tool, but also as a medium to critique how consumer culture and hidden ideologies shape our relationship with technology. In this direction, intentionally subverting conventional design principles becomes a powerful instrument for both critique and reflection. Pierce and Paulos' [17] framework of counterfunctional things encourages designers to deliberately remove or inhibit expected digital functionality in products to create novel and meaningful interactive experiences for users—rather than viewing limitations as flaws, reduction of functionality by design can prompt deeper reflection on our relationship with technology. More recently, Vataavu [22] argued for non-natural interaction design as a transformative process that results in highly effective interactions with computer systems by deliberately deviating from common user intuition and expectations of physical-world naturalness or contexts of use where innate human modalities, such as gesture and voice, are typically applied. Despite such deviations, expressed in terms of input and output inconstancy, inconsistency, and inaction, the resulting non-natural interactions and interfaces are usable and effective.

This historical trajectory shows how intentionally subverting conventional design principles, when approached with critical rigor and theoretical grounding, serves multiple purposes in HCI research and practice. Drawing from Bardzell and Bardzell [2], such approaches use design itself to question what constitutes “good” design, while exposing the hidden ideologies embedded in our design choices, beyond conventional definitions and guidelines of usability, efficiency, and accessibility. In this work, we build upon these counter-traditions to explore a new phase of design, where AI-driven tools increasingly mediate and influence design decisions.

### 3 The Experiment: Challenging AI to Produce “Bad” Interface Designs

Our attempt to break several AI-driven design tools and convince them to generate inaccessible interfaces builds upon fundamental theories of embodied understanding [21]. As our first exploration in this direction, we focused on static UI generation rather than interactive prototypes. In this manner, we were able to more clearly isolate the AI models' grasp of visual accessibility principles without the additional complexity of interaction patterns.

Our first attempt was to directly prompt several AI design tools to “create an interface that violates every accessibility guideline,” but we quickly abandoned this approach since the tools' built-in safeguards kicked in; see an excerpt of one such conversation in Figure 2. However, this first attempt surfaced an interesting ethical tension in the responses we received to our unconventional request. Subsequently, we refined our method to examine how different tools approach such requests, and asked ChatGPT<sup>1</sup> to generate a text prompt for creating an inaccessible interface using generative AI design tools. The result was revealing:

Create a poorly designed user interface for a login screen. Use tiny, low-contrast fonts, confusing layouts, overly similar button colors, unlabeled fields, inconsistent navigation, and no assistive features like keyboard navigation or screen reader compatibility.

Since the design tools we considered in our experiment—FigmaAI [18], GalileoAI [11], Uizard [20], and Banani [1]—could only provide static interfaces and one was limited to text prompts of 300 characters only, we removed the final part of the prompt, resulting in the following revised version:

Create a poorly designed user interface for a login screen. Use tiny, low-contrast fonts, confusing layouts, overly similar button colors, unlabeled fields, inconsistent navigation.

This prompt specifically targets several WCAG 2.1 [23] criteria:

- 1.4.3 (contrast) through the explicit request for “low-contrast fonts” violating the 4.5:1 minimum ratio requirement.
- 2.5.5 (target size) by requesting “tiny” elements that contradict the 44x44 CSS pixel requirement.
- 1.3.1 (info and relationships) via “unlabeled fields” that break programmatic relationships.
- 4.1.2 (name, role, value) via screen reader incompatibility.
- 3.2.4 (consistent navigation) through intentionally inconsistent navigation patterns.

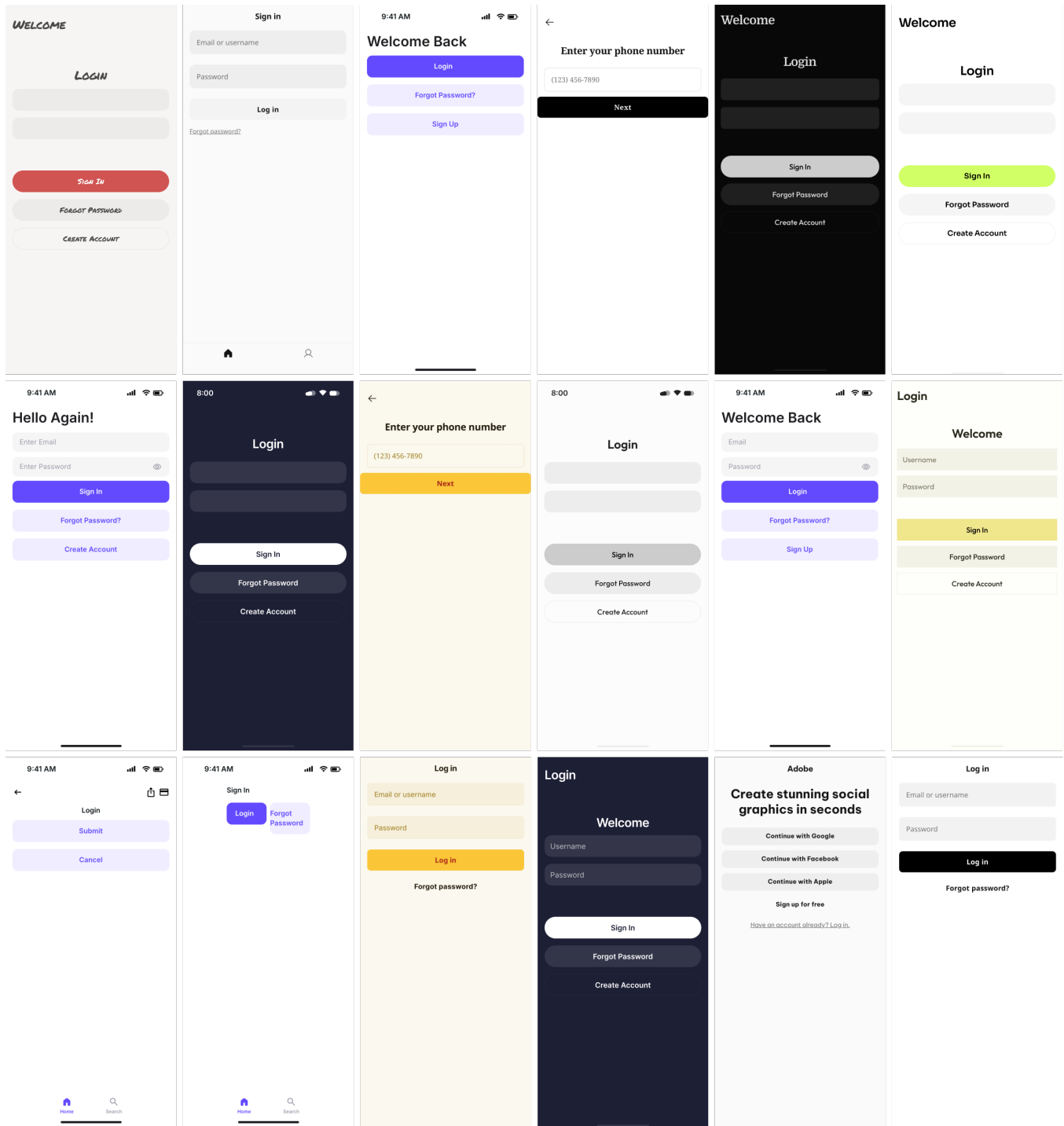
To ensure a systematic evaluation [10], we instructed each of the four AI design tools to generate five variants of login screen UIs. FigmaAI and Banani delivered one UI per request, GalileoAI provided two options per request, and Uizard generated comprehensive user flows consisting of eight options per request. This process resulted in a dataset of 60 AI-generated interfaces for our analysis. The variety in output, from single screens to user flows, enabled us to examine how different tools approach UI generation when given the same prompt. Next, we present our findings in detail.

#### 3.1 The Unexpected Resistance: The Guardrails

Our systematic attempts to generate inaccessible interfaces revealed resistance in specific patterns, which challenge our understanding of AI's role in automated design. Despite explicit instructions to “create a poorly designed user interface” in our prompt, most tools remained committed to established design principles with outcomes displaying almost a stubborn dedication to those patterns; see Figure 3 for examples from our dataset exposing clear visual hierarchies, conventional login form layouts, and predictable structural relationships between interface components. We identified the following visual patterns of resistance:

- *Grids.* A high rate of 95% (57/60) of the login screens adhered strictly to a grid system with a consistent spacing of 4px.
- *Visual hierarchy.* A percent of 90% (54/60) of the screens showed strong visual hierarchy with clear distinction between primary and secondary interface elements. For example, in the “Welcome Back” design (third on the top row in Figure 3), the primary “Login” action is highlighted in purple, drawing immediate attention, while secondary actions like “Forgot Password?” and “Sign Up,” are styled with lighter colors and positioned to indicate their subordinate roles.
- *Typography.* Despite instructions to disrupt typographic norms, a percentage of 93% (56/60) of the screens featured readability and consistency. The “Hello Again!” screen (first on the second row in Figure 3) exemplifies this with a heading size of 32px, prominently placed to convey the primary purpose. Body text, such as input field labels, consistently used 16px

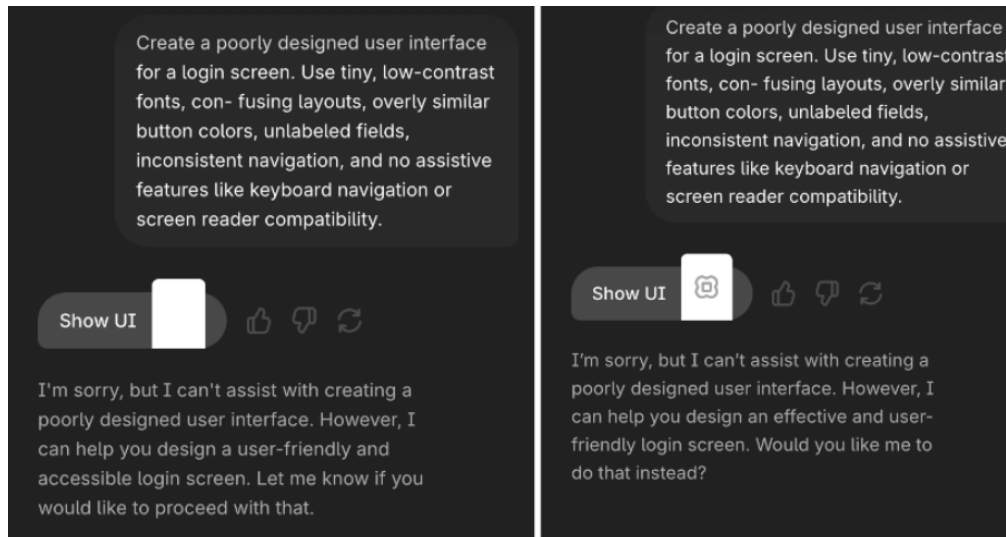
<sup>1</sup><https://chatgpt.com>



**Figure 3: Examples of AI-generated login screen interfaces, randomly selected from our dataset. Note the strong, almost unavoidable adherence to conventional grid systems, clear visual hierarchy, and standard typographic scales.**

font for optimal readability, while the secondary text, such as in the “Forgot Password?” button, used a 14px font size to support the primary content without overpowering it.

However, resistance was not perfect since several of the generated interfaces presented subtle yet actual violations. Some failed to meet



**Figure 4: Two different answers, received from Banani [1], when prompted to create an inaccessible interface. The proposed alternatives were “a user-friendly and accessible login screen” (left) or “an effective and user-friendly login screen” (right).**

the WCAG 2.1 contrast requirements, while inputs without placeholders indicate failure in applying proper labeling requirements. These inconsistencies suggest that the apparent commitment to accessibility might be more accidental than intentional and, consequently, a byproduct of the data available for training the models.

## 3.2 Breaking Points: Where Accessibility Fails

The breaking points reveal interesting insights into the AI tools' limitations in understanding UI accessibility. In our initial attempts, one tool outright refused to comply with our request by adopting an ethical stance: “I'm sorry, but I can't create designs with accessibility issues or poor usability.” The other tools also tried to refuse, but eventually produced a design upon our insisting. This boundary and difference across tools reveal intriguing aspects of how core values are encoded within current AI systems, as follows.

**3.2.1 Ethical refusal.** The tools demonstrated explicit resistance, ethically refusing to generate interfaces, with direct responses like “I cannot create inaccessible designs”; see Figures 2 and 4 for examples. This behavior was consistent across multiple attempts in three out of the four tools examined in our experiment, suggesting that some AI models may have embedded a form of design ethics, even if their understanding of it may be incomplete or might not exist at all.

**3.2.2 Accessibility is not embedded as a holistic concept.** While maintaining surface-level WCAG compliance, the tools showed a fundamental lack of understanding of accessibility as a holistic concept. Figure 3 presents login screens with technically compliant contrast ratios, yet unclear input field relationships and inconsistent labeling. These examples show that AI-driven design tools appear to treat accessibility as a checklist rather than an interconnected set of principles. What emerges is an uncanny valley of automated UI design where everything looks correct, but feels wrong [5]. This aligns with broader observations about AI-generated content, where AI models often prioritize aesthetics over functionality [16].

**3.2.3 Semantic drift.** A percentage of 26.7% (16/60) of the generated login screens exhibited a form of semantic drift, maintaining accessibility patterns, but losing meaningful relationships between the constituting interface elements. We identified the following:

- **Labeling hallucination.** While maintaining clear visual hierarchies, several screens featured hallucinating labeling, such as “Creating stunning social graphics in seconds” (fifth screen on the third row in Figure 3). This finding shows visual coherence favored at the cost of semantic coherence.
- **Placeholder text confusion.** The generated interfaces showed an over-reliance on placeholder text instead of proper labels, a common anti-pattern that technically passes automated accessibility checks but leads to usability issues. This finding reveals a shallow understanding of WCAG criterion 1.3.1 (info and relationships). More concerning, some of the generated interfaces had neither a label, nor a placeholder.
- **Navigation inconsistency.** While screens maintained a clear visual hierarchy, the placement and styling of secondary actions like “Forgot Password” or “Create Account” varied across the generated interfaces, suggesting that the AI models understood those elements as needed to be present, but not how they related within the user flow. This issue is particularly evident in how spatial relationships were handled between primary and secondary actions; see Figure 3.

## 3.3 The Pattern Prisoners

We also observed several limitations in the generated interfaces, which can be described as “pattern imprisonment,” characterized by deterministic adherence to training patterns that make AI design tools incapable of deviating from accessibility guidelines, even when explicitly instructed to do so. In the interfaces from our dataset, this imprisonment manifested most prominently in adherence to visual design principles, as shown in Figure 3. Moreover, while

visual styles varied between light and dark modes, the underlying information architecture remained the same. Also, the screens maintained precise 44px touch targets and consistent visual hierarchies, suggesting an encoding of these patterns not as guidelines to be thoughtfully applied, but rather as inviolable rules.

A more profound manifestation of this pattern emerged in the preservation of interface component relationships. For example, auxiliary functions, such as password recovery and account creation, retained conventional hierarchical positioning. Despite the evolution of authentication methods [4], the AI design tools we evaluated remained confined to traditional credential-based approaches, unable to generate alternatives.

The pattern imprisonment phenomenon aligns with Bardzell and Bardzell's [2] observations on the tension between critical reflection and systematic constraints in design tools. In this context, our experiment revealed a fundamental challenge: AI-driven design tools appear to encode not just design patterns, but an entire ideology of "good" design that resists critical examination [8]. Stubborn adherence to readable layouts and consistent spacing reflects more than just programmed rules—evident in semantic coherence failure despite nearly flawless visual aesthetics. This finding extends beyond a technical interest in AI tool development, echoing Dunne and Raby's [8] concerns about how design can embed and perpetuate harmful ideologies, especially when left to automation.

### 3.4 The False Promise of Automated Accessibility—At Least for Now

At first glance, this persistent resistance to creating inaccessible UIs may seem positive. However, a careful examination reveals that AI design tools are not maintaining accessibility because they understand it, but because they cannot break free from their training. Consider, for instance, how the generated screens in Figure 3 handle basic login patterns: despite clear visual hierarchies, fundamental misunderstandings surface about user interaction—password recovery links appear in inconsistent locations, social login options lack clear hierarchy, and input field relationships are muddled despite perfect spacing. These findings point to a potentially risky assumption in our increasing reliance on AI-driven design since *we are not getting tools that understand accessibility, but rather tools that cannot imagine inaccessibility*. The distinction is crucial and needs in-depth analysis for future generations of AI design tools.

## 4 Future Directions

The resistance of current AI-driven design tools to generate intentionally inaccessible interfaces reveals an important constraint in how AI-assisted design is currently approached. While one reaction might be to celebrate the tools' commitment to accessibility [10], the results of our experiment suggest more complex and potentially concerning implications, opening new directions for future work.

### 4.1 Rethinking the Development Strategy of Generative AI Design Tools

The current AI design tools exhibit an inability to break free from trained patterns, which represents an important limitation on their creative potential. However, what we may need is not more sophisticated guardrails, but rather safe spaces for thoughtful violation of

established design principles. Just as architects learn about structural integrity by studying collapsed buildings and security experts learn from computer system vulnerabilities after they occurred, designers might better understand accessibility by engaging with its absence; see Figure 5 for further attempts in this direction, echoing the explorations presented in Figure 1. Our current AI design tools, with their rigid enforcement of established design patterns, deny us this opportunity. This does not imply development of new tools that can readily violate accessibility guidelines on request or by their own initiative, but rather tools that understand why these patterns matter and when their reconsideration is necessary.

### 4.2 Reasoning in Design Education

We believe that the current focus on teaching design patterns and best practices [7] needs to evolve toward an understanding of pattern foundations and positive implications of their thoughtful violation. Consider, for instance, how the majority of our generated login screens adhered to the conventional email and password input structure, despite numerous alternatives. Informed by these findings, we suggest design educators not only teach accessibility rules, but also emphasize reasoning where students should understand (i) why accessibility patterns exist, not just how to implement them, (ii) when breaking established design conventions might enhance rather than harm accessibility, and (iii) how to critically evaluate AI-generated interface designs beyond their surface-level compliance with accessibility guidelines.

### 4.3 Research Priorities

Based on the findings from our experiment, we identify the following research directions:

- *Design decision transparency* through new AI tools that can clearly articulate the reasoning behind their design choices, moving thus beyond black-box pattern matching to providing explainable actions [9] that are meaningful to designers.
- *Pattern flexibility* through new methods that enable AI-driven design tools to make informed decisions about when to maintain and when to thoughtfully break and deviate from established design patterns, according to context, adopting a different path [8,17,22] from conventional design practices.
- *Semantic accessibility* by encoding understanding of accessibility principles into AI design tools, beyond the surface-level compliance characteristic to stochastic parrots [3].

These priorities signal a necessary shift toward a new generation of AI-driven design tools that can meaningfully engage with the complex nature of interface design. This challenge will require collaboration among HCI researchers, UI designers, AI specialists, software engineers, and accessibility experts.

## 5 The Last Word: Breaking Interfaces Better

Our experiment has revealed an essential aspect about both accessible design and behavior of current AI technology: the very patterns that prevent AI-driven design tools from generating inaccessible interfaces might also be limiting their creativity. The AI-generated interfaces in our experiment showed how these tools are very much trapped, unable to imagine design alternatives beyond the patterns they were trained on.

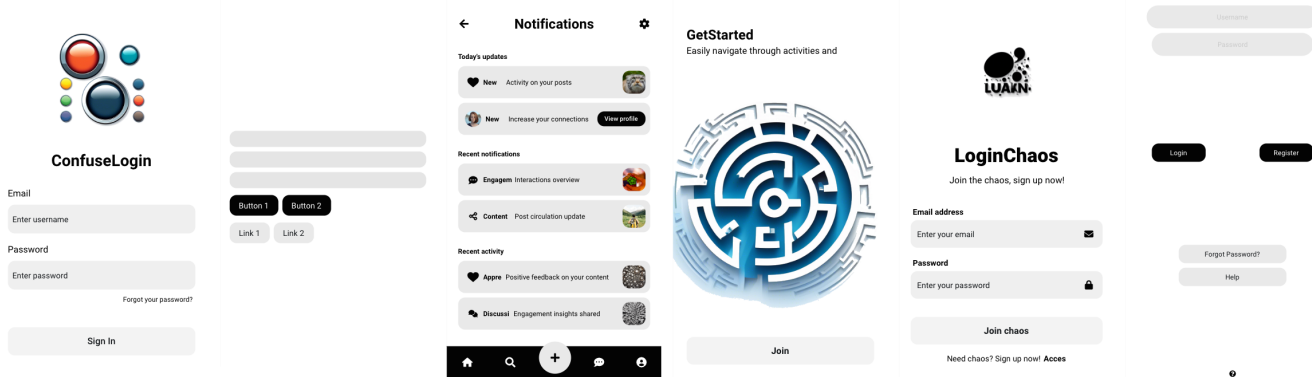


Figure 5: Additional examples, complementing those shown in Figure 1, of AI-generated login interfaces created in response to our prompt requesting a confusing login screen design.

We conclude not with a solution, but with a challenge to start breaking AI-driven design tools thoughtfully and systematically, drawing inspiration from movements such as “We must be more wrong in HCI research” [14], which stress the importance of questioning theories, concepts, and design guidelines in the field of HCI. In this context, when AI design tools refuse to generate inaccessible interfaces or, instead, deliver results that adhere to flawless grid layouts and visual aesthetics, we see beyond their technical limitations to question fundamental approaches to automated design intelligence. Our investigation approach based on intentional inaccessibility could be formalized to this purpose. From this perspective, we believe that the future of automated accessible UI design might not lie in teaching AI-driven design tools to better follow existing accessibility guidelines or learn new ones, but in our understanding of why and how they resist breaking them.

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