Master Media Technology

PromptlyUX: An AI-Driven UX/UI Design Prompting Assistant

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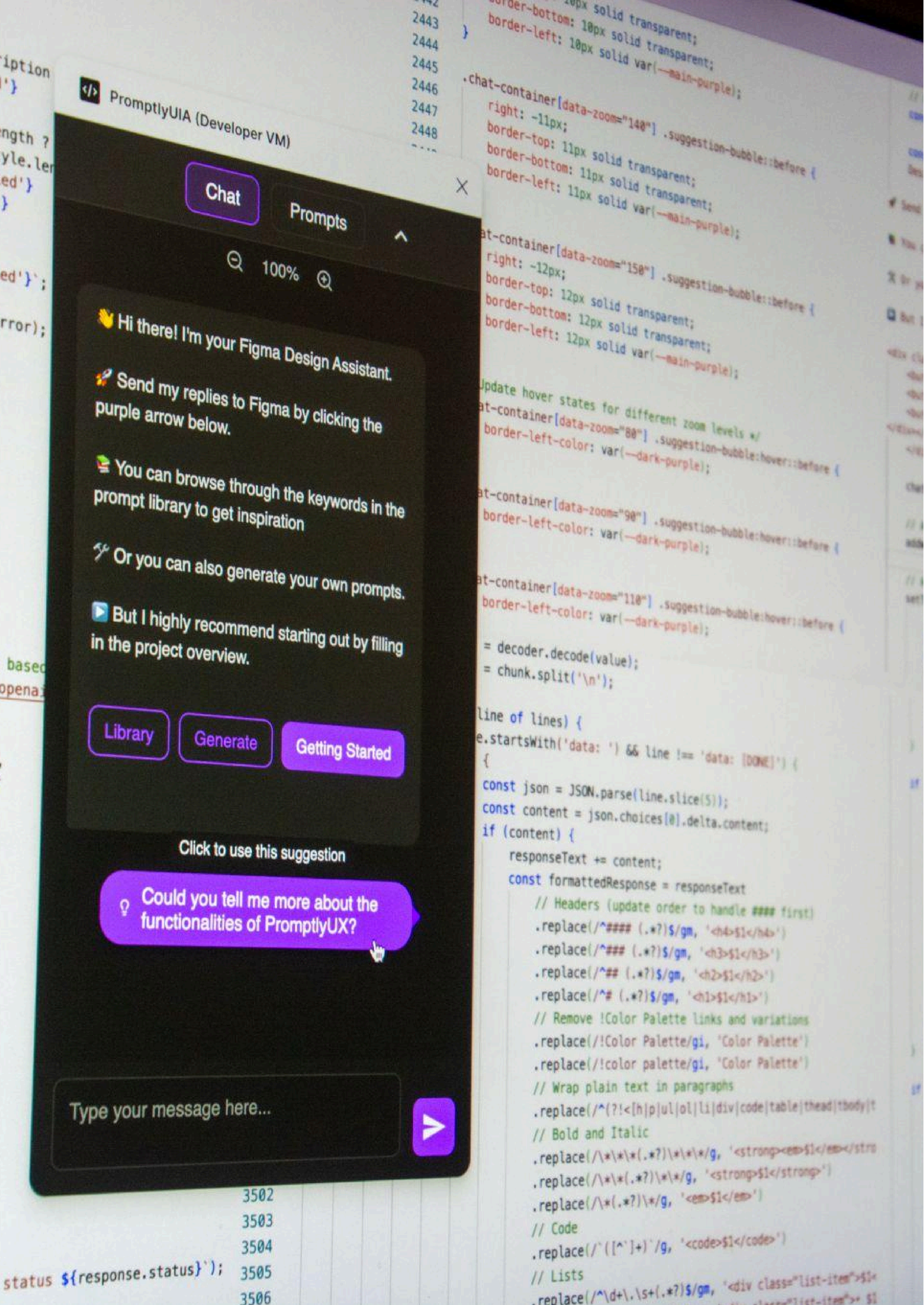
PromptlyUIA (Developer VM)
Chat
Prompts
100%
👋 Hi there! I'm your Figma Design Assistant.
🚀 Send my replies to Figma by clicking the purple arrow below.
📚 You can browse through the keywords in the prompt library to get inspiration
🛠 Or you can also generate your own prompts.
▶️ But I highly recommend starting out by filling in the project overview.
Library
Generate
Getting Started
Click to use this suggestion
Could you tell me more about the functionalities of PromptlyUX?
Type your message here...
.chat-container[data-zoom="140"] .suggestion-bubble::before {
right: -11px;
border-top: 11px solid transparent;
border-bottom: 11px solid transparent;
border-left: 11px solid var(--main-purple);
border-left-color: var(--dark-purple);
= decoder.decode(value);
= chunk.split('\n');
const json = JSON.parse(line.slice(5));
const content = json.choices[0].delta.content;
if (content) {
responseText += content;
const formattedResponse = responseText
// Headers (update order to handle #### first)
// Remove !Color Palette links and variations
.replace(/!Color Palette/gi, 'Color Palette')
.replace(/!color palette/gi, 'Color Palette')
// Wrap plain text in paragraphs
// Bold and Italic
// Code
// Lists
status ${response.status}`);

Abstract

As generative AI becomes increasingly integrated into design workflows, many UX/UI practitioners face a critical barrier: the challenge of formulating effective prompts for large language models (LLMs). This thesis introduces the concept of "prompt literacy" to describe this gap in user understanding and interaction, particularly among designers unfamiliar with AI conventions. In response, this research presents PromptlyUX, a custom-built Figma plugin designed to support prompt formulation through structured, contextual guidance. PromptlyUX offers a suite of integrated features, including a guided onboarding questionnaire for project scoping, dynamic follow-up prompt suggestions that evolve with user input, and a categorized prompt library grounded in UX terminology and design thinking principles. To evaluate the effectiveness of PromptlyUX, a remote between-subjects user study was conducted, comparing the plugin against a baseline AI chat interface. Participants were tasked with completing a design challenge covering multiple stages of the UX process. The study measured outcomes related to usability, cognitive workload, satisfaction, and reuse intent using validated scales (SUS, NASA-TLX) and follow-up interviews. Results show that structured prompting assistance significantly enhanced participants' perceived efficiency, reduced mental demand, and increased satisfaction and willingness to adopt AI in future workflows.This thesis contributes to the growing discourse on human-AI collaboration in creative fields by demonstrating how prompt engineering can be intentionally embedded within design tools to bridge technical and conceptual gaps. PromptlyUX exemplifies a user-centered approach to AI integration transforming prompting from a barrier into a productive, collaborative interaction. The findings offer practical design implications for improving AI usability in creative domains and help shape emerging best practices in AI-assisted UX/UI design.

Acknowledgments

I would like to express my gratitude to the people who supported me throughout this thesis journey, and also my academic career. First and foremost, thank you to Rob for keeping me grounded while I was constantly floating through every phase of this process. Your calm presence and guidance helped anchor my thinking when I needed it most. To Tim, thank you for generously sharing your deep practical knowledge of artificial intelligence during the workshops, your insights were instrumental in shaping both my understanding and the direction of PromptlyUX. A special appreciation to my parents, whose unwavering support, both emotional and financial, made this thesis (and so much more) possible. Hopefully as of now your last child will finally no longer be a financial burden. Then to my dearest Aleks, thank you for keeping me fed and functioning throughout; as I basically turned into a human Tamagotchi the last few weeks. And to my homie Chiini, who has been there since the very first day of User Experience Design: I wouldn't have made it without you, but then again, I also would have never done this masters without you… Lastly, to all the friends made along the way, from the bachelor's to the master's, thank you for shaping this journey into something far richer than any curriculum could offer. I've learned more from the conversations, collaborations and shared chaos with you than from any course I've taken. We are all in this together (Efron et al., 2006).

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1. Introduction

As a user experience designer I have long been captivated by the challenge of solving complex pain points through design. The act of interpreting user behavior, uncovering pain points and then translating these into seamless digital interactions or interfaces has always felt like assembling a deeply human puzzle with creativity. The moment a user encounters a design element they didn't know they needed only to express sincere appreciation for how it improves their experience is what keeps me motivated and passionate about this field. The rapid emergence of artificial intelligence (AI) has introduced both disruption and opportunity into this domain. Like many designers I initially approached AI with skepticism. However, through further exposure and experimentation it became clear that, much like the printing press or the internet, AI represents a paradigm shift that will only grow more sophisticated. Realizing that its current limitations will even be the least refined versions we will ever encounter, I chose to embrace AI not as a threat, but as an extension of my (design) capabilities. I now actively explore how these systems can optimize my creative process from automating repetitive daily tasks to fine-tuning personal workflows using multiple AI platforms trained on my own project data and working context.

This shift in mindset also illuminated a growing divide: while I had immersed myself in AI tools, many of my peers remained hesitant or uncertain about where to begin. A common barrier appeared to be the lack of structured guidance for engaging with open-ended AI interfaces. Writing prompts from scratch, especially for those unfamiliar with natural language interaction models, often led to frustration or abandonment. Simultaneously, I discovered through research that even AI developers struggle to explain the inner workings of large language models (LLMs). The phenomenon of the AI "black box" highlights a critical challenge: these models produce impressively human-like output, yet the logic behind individual responses remains largely opaque, even to their creators (Liao et al., 2023). This realization led me to identify a unique opportunity. Rather than attempting to explain or demystify the model's internals, I aimed to bridge the gap between my peers (designers) and AI systems through domain-specific prompting support. Prompt engineering, the practice of crafting precise instructions for LLMs, has become a crucial skill for unlocking the potential of generative AI in creative fields.

This thesis explores that vision through the development and empirical evaluation of PromptlyUX, a custom-built Figma plugin that provides structured prompt guidance to support AI-assisted UX/UI design. The tool includes features such as an onboarding survey, dynamic follow-up prompts, regenerable suggestion tabs, and a domain-specific prompt library, all designed to lower cognitive effort, improve prompt fluency, and enhance human-AI collaboration. PromptlyUX positions AI not as a distant system to command, but as a creative collaborator embedded within the designer's environment. In doing so, this research responds to a well-defined gap in current design literature and practice. While AI tools are increasingly prevalent in design workflows (Song, Zhu, & Luo, 2024), there remains limited focus on supporting the human side of interaction, particularly through contextualized, actionable prompting frameworks. By grounding this work in both theoretical literature and real-world user testing the study aims to contribute to knowledge around AI-integrated UX workflows, prompt engineering, and human-centered tool design.

The remainder of this thesis is organized to guide the reader through the theoretical foundations, methodological approach, and empirical findings of the study. Chapter 2 reviews the relevant literature, including key developments in UX design, the integration of artificial intelligence, prompt engineering practices, and the current landscape of AI-assisted design tools. Chapter 3 outlines the research problem, objectives, and guiding research questions that shaped the investigation. Chapter 4 presents the development process of the PromptlyUX plugin alongside the experimental methodology used to evaluate its effectiveness. Chapter 5 reports the results of the study, drawing from both quantitative and qualitative data sources. Chapter 6 interprets these findings in relation to existing scholarship, exploring their broader implications. Finally, Chapter 7 concludes with a summary of key contributions, acknowledged limitations, and suggestions for future research directions.

2. Related Works

This chapter provides an overview of the theoretical and empirical foundations relevant to this thesis, with a focus on the intersection of User Experience (UX) design and Artificial Intelligence (AI). As AI technologies, particularly large language models (LLMs), gain traction in design workflows, it becomes increasingly important to understand both the evolution of UX as a discipline and the implications of AI integration. The sections that follow explore the historical development of UX design practices, recent paradigm shifts enabled by AI, the emergence of prompt engineering as a critical interface between human and machine creativity, and the current landscape of AI-assisted design tools. Together, these perspectives reveal a growing gap between the capabilities of AI systems and the needs of designers, particularly in the area of prompt formulation and interaction design.

2.1 User Experience Design

User Experience (UX) design was first coined by Donald Norman in the mid-1990s, marking UX design's emergence as a distinct discipline that pushed beyond conventional usability concerns toward a more holistic view of how humans interact with systems (Norman et al., 1995). UX design entails the entire process of creating products that provide meaningful, relevant, and enjoyable experiences for users. It extends beyond the visual interface to include all aspects of user interaction, considering users' emotions, beliefs, preferences, perceptions, and behaviors throughout their engagement with a product or service (ISO 9241-210:2010, as cited in Stige et al., 2024). Research consistently demonstrates that effective UX implementation correlates with enhanced user satisfaction, improved retention rates, and stronger commercial outcomes (Hassenzahl & Tractinsky, 2006). Conversely, inadequate attention to UX frequently results in decreased satisfaction, higher task abandonment, and negative user evaluations (Badran & AL-Haddad, 2018; Rizvi, 2022). This evidence underscores that investing in UX optimization is not merely an aesthetic consideration but a strategic business necessity.

The typical UX design workflow follows the Design Thinking methodology, an iterative, non-linear process that provides a solution-based approach to solving complex problems (see Figure 1). This process typically encompasses five distinct phases: Empathize, Define, Ideate, Prototype, and Test (Yudhanto et al., 2022). During the Empathize phase, designers immerse themselves in understanding users through research techniques such as interviews, surveys, and observation. The Define stage involves synthesizing research insights to articulate specific user problems. In the Ideate phase, designers generate a wide range of creative solutions. These concepts are then transformed into tangible representations during the Prototype phase, ranging from low-fidelity sketches to high-fidelity interactive models. Finally, the Test phase involves rigorous evaluation with representative users to validate design decisions and identify areas for refinement (Padmasiri et al., 2023). This cyclical process continues throughout product development, ensuring continuous improvement based on user feedback, data analyzation and other key metrics.

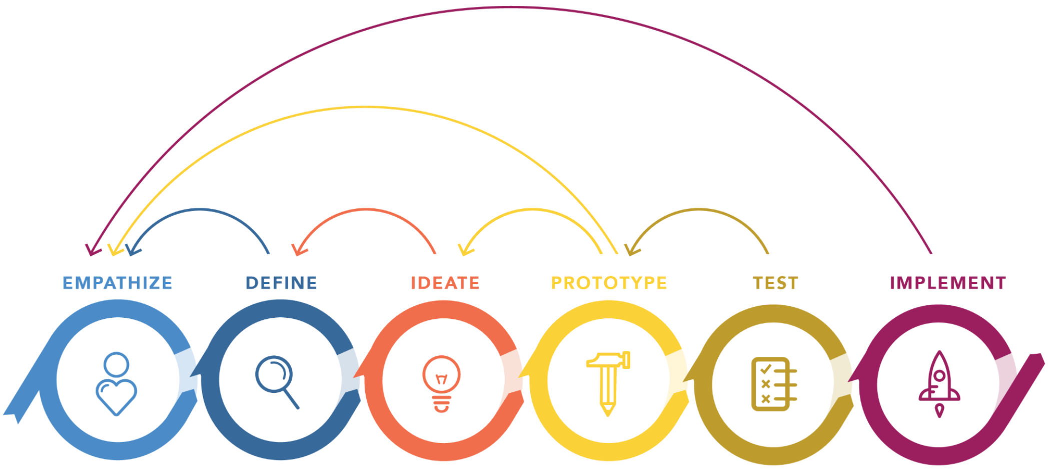


Figure 1. Design Thinking Process by NNGROUP.COM

UX designers are responsible for translating research insights into intuitive interfaces that anticipate user behaviors and preferences. Designers should balance aesthetic considerations with functional requirements, ensuring that each element serves a purpose within the larger user journey. Their expertise encompasses not only visual design principles but also cognitive psychology, information architecture, and interaction patterns. Effective UX designers must continuously empathize with diverse user perspectives, identifying pain points that users themselves might not articulate. As products become increasingly complex, designers must navigate competing stakeholder priorities while maintaining a steadfast focus on user-centered outcomes. This multifaceted role requires both technical proficiency and creative problem-solving abilities, positioning designers as essential advocates for user needs throughout the product development lifecycle.As digital products grow increasingly complex, UX designers face mounting challenges in creating cohesive experiences across multiple platforms and touchpoints. The proliferation of design tools, methodologies, and best practices has created a need for more sophisticated supportive systems (Gong et al., 2024).

2.2 AI Integration & Paradigm Shifts

Empirical research by Yang Xu et al. (2024) reveals widespread AI adoption in the FinTech sector, with 78% of surveyed companies implementing AI in their UX/UI design processes over the past two years. These companies are leveraging AI technologies primarily for personalization, predictive analytics and natural language processing. The impact of these implementations has been substantial according to this study: with AI-enhanced applications demonstrating a 41% increase in daily active users compared to only a 17% increase in apps with limited AI integration. These findings showcase not only the growing importance of AI in improving user engagement, but also signal a broader shift in the role of AI within the design process itself. This shift reflects a profound evolution in how digital products and services are conceived and developed through the integration of Artificial Intelligence (AI) into User Experience (UX) design (Niforatos, Ferwerda, Pop, & Schricker, 2024). Early explorations primarily focused on automating isolated tasks, such as generating layout alternatives or analyzing usability metrics (Khan, Shokrizadeh, & Cheng, 2025). However, advancements in machine learning and data-driven design tools have progressively reshaped the landscape, shifting from simple assistance towards more complex, integrated solutions. Recent academic literature (Stige et al., 2024; Wells, 2024) emphasizes that AI is not just enhancing existing UX processes, but is fundamentally transforming them. Systematic reviews showcase how AI-driven tools enhance efficiency and accuracy while opening new possibilities for creative exploration and design innovation.

Wei Xu (2023) contextualizes this transformation as a paradigm shift within the broader evolution of UX design. According to Xu, UX 1.0 (late 1980s to 2007) prioritized functionality and usability in standalone products. Think of websites and desktop software, where the main focus was on making buttons and screens usable. This evolved into UX 2.0 (2007–2015), which emphasized holistic user experiences across multiple touchpoints. Designing for mobile phones and touchscreens, which are more complex because they involve apps, services, and flows. The current paradigm, UX 3.0 (2015 onwards), is defined by the pervasive influence of AI, big data, and intelligent ecosystems. This consists of interconnected smart devices and AI-driven systems that shape how users interact with technology in daily life. Xu’s framework identifies four key dimensions of this new paradigm: the expansion of UX across interconnected devices and contexts; the use of AI to uncover latent user needs and foster human-AI collaboration; the enhancement of design workflows through intelligent, adaptive tools; and a focus on building trust and ethical interactions via explainable, user-centered AI systems. The UX 3.0 paradigm presents both opportunities and responsibilities. While it enables more advanced data-driven design processes, failure to adapt risks producing confusing or even harmful user experiences, eroding public trust in technology, and missing critical opportunities for innovation. Xu (2023) argues that designers must extend their focus beyond interface aesthetics to embrace the complexity of intelligent ecosystems.

Supporting this perspective, Abbas et al. (2022) demonstrate that machine learning (ML) offers significant potential for automating repetitive tasks, generating diverse design options, and providing actionable, data-driven insights. Yet, they also emphasize that these benefits come with challenges, including the technical complexity of implementing ML models, inherent biases in training data, and the growing demand for designers to acquire technical literacy in AI systems. Liang et al. (2023) further explore the evolving interplay between AI and UX design workflows. Their research illustrates how AI accelerates traditional design tasks by analyzing user data to create profiles, refining rough sketches, predicting usability issues, and even generating code from prototypes. However, they caution against overestimating AI's capabilities, as current systems lack emotional understanding and creative intuition. AI can misinterpret design intent or fail to capture subtle human-centered nuances. Liang et al. (2023) advocate for viewing AI not as a replacement but as a co-pilot, a powerful assistant that automates routine processes while preserving human designers' critical role in creative decision-making and empathetic design. Their work points to future research areas, including defining the optimal boundaries of automation, identifying emerging skill sets for designers, and addressing ethical concerns such as privacy and dependency on AI systems.

Moreover, the inherently multidisciplinary nature of UX design, combining psychology, visual communication, and interaction design, creates fertile ground for AI-enhanced tools that support prompt-driven knowledge retrieval and real-time application. Tools embedded within platforms like Figma, Adobe Creative Cloud, and other design environments are already leveraging AI to propose design solutions, generate content, and assist with user research, enabling designers to work more efficiently while maintaining creative control.

In summary the integration of AI into UX design represents an ongoing, transformative shift from isolated tools to fully embedded, collaborative systems that enhance rather than replace human creativity. This co-pilot model emphasizes a symbiotic relationship between designers and AI, empowering practitioners to navigate the complexities of intelligent systems while ensuring that user experiences remain human-centered, ethical, and innovative.

2.3 Prompt Engineering

Despite the potential of AI-based various approaches, it’s becoming increasingly evident that solutions utilizing Large Language Models (LLMs) are at the forefront of this technology’s application. LLMs are now among the most commonly implemented forms of AI, and they rely heavily on the quality of prompts provided to them (Naveed et al., 2023). LLMs can excel at numerous natural language processing tasks, such as text summarization, question answering, text classification, information extraction and conversational dialogue generation, when appropriate instructions are used. Yet these models are remarkably sensitive to how prompts are constructed (Matarazzo & Torlone, 2025), and developing effective prompts typically demands significant manual effort through what is known as "prompt engineering." Those without AI expertise often find it particularly challenging to clearly communicate their intended tasks to LLMs, leading to prompt engineering that tends to be improvisational rather than methodical (Zamfirescu-Pereira et al., 2023). Current tools have open-ended prompt inputs and thus require designers to master prompt syntax, creating a "prompt literacy gap" Garg (2024) that disproportionately affects novice users.

Recent empirical studies show that UX designers are incorporating Large Language Models (LLMs) into various stages of their design workflows and with that leveraging their capabilities to enhance productivity, ideation, and creativity (Takafoli et al., 2024; Stige et al., 2024). Designers use LLMs like ChatGPT for early-stage ideation, generating interface concepts and exploring alternative interaction patterns (Zhou et al., 2024). In the copywriting phase, LLMs assist in drafting UX microcopy, summarizing technical documentation, and adjusting tone for different audiences (Li et al., 2024). They even support wireframe generation offering quick low-fidelity layout options and even making these designs responsive across different screen sizes (Feng et al., 2024).

Moreover, LLMs facilitate the creation of user personas especially in data-scarce situations by synthesizing research inputs into coherent persona descriptions (Huang, 2024). While these tools empower designers, they showcase the need for structured prompting practices as the quality and relevance of outputs remain highly dependent on prompt clarity, specificity, and context (Zhou et al., 2024; Li et al., 2024). The evolving role of LLMs in UX design accentuates prompt engineering as a technical skill and as a communicative bridge between design intent and machine interpretation. Difficulties around this bridging have started the development of automatic prompt engineering as an emerging research area, with significant approaches involving the use of LLMs themselves to generate and optimize prompts (Zhou et al., 2023b). Effective prompt engineering involves crafting precise inputs to generate desired outputs from AI systems, functioning as a form of communication protocol between humans and language models. The quality of prompts significantly impacts the relevance and utility of AI-generated responses, with well-structured prompts yielding more accurate and contextually appropriate outputs (Zhou et al., 2023; Valentine, 2024). The practice ƒextends beyond simple query formulation, encompassing strategies such as context specification, step-by-step reasoning templates, and structured formats that guide AI systems toward generating specific types of content (Ye et al., 2023)

The effectiveness of prompt engineering is particularly evident in specialized applications, such as those discussed by Ye et al. (2023), where domain-specific knowledge must be extracted from general-purpose models like LLMs in UX/UI design. Zhou et al. (2023) found that automated prompt engineering can, in some cases, outperform human-crafted prompts, highlighting the value of systematic approaches to prompt creation. While some findings suggest that prompt engineering may be evolving from an ad hoc practice into a more structured discipline with established principles and techniques, this should be viewed as a potential trajectory rather than a definitive trend. An alternative path could emerge in which advances in the “deep reasoning” capabilities of LLMs lessen the need for prompt engineering altogether. At the same time, Sarkar et al. (2023) introduced "participatory prompting" as a collaborative approach to prompt development, emphasizing iterative refinement and user feedback in crafting effective prompts for complex tasks. Together, these perspectives illustrate both the evolving landscape and the ongoing debate about the future role of prompt engineering in human-AI collaboration.

In the context of User Experience (UX) design, prompt engineering addresses several domain-specific challenges. UX designers frequently need to translate between visual concepts and verbal descriptions, requiring prompts that effectively communicate design intent in natural language (Valentine, 2024). Garg and Rajendran (2024) noted that structured prompts can significantly improve learning outcomes in technical domains, suggesting similar benefits for UX practitioners developing new skills or exploring unfamiliar design patterns.

Despite its potential benefits, effective prompt engineering in UX contexts remains challenging. Technical limitations of AI models, the complexity of design requirements, and the need for specialized knowledge all contribute to the difficulty of creating effective prompts for design tasks (Ye et al., 2023). These challenges indicate a need for specialized tools and frameworks that support UX designers in developing and managing effective prompts for AI-assisted design work.

2.4 AI-Assisted Tools

Tools like Uizard and Galileo AI enable rapid UI prototyping by converting text prompts into layouts. However, their outputs are often generic, lacking adaptation to project-specific goals or user needs (Nielsen Norman Group, 2023; Zhou et al., 2023). Similarly, platforms such as UserTesting AI Insights apply LLMs to analyze interview transcripts, yet struggle with capturing emotional nuance and context-dependent meaning (Khan, Shokrizadeh, & Cheng, 2025). In the domain of accessibility, plugins like Stark and Ablely use LLMs to flag WCAG compliance issues. While effective for standard checks, they often miss subtler, contextual violations (Padmasiri et al., 2023), reinforcing the notion that LLMs function best as assistants rather than autonomous evaluators.

Gong (2024) emphasizes the need for AI systems to serve as creative collaborators rather than automated tools. Designers increasingly treat AI as a partner in divergent thinking, generating alternatives, iterating quickly, and enhancing ideation (Khan et al., 2025). This shift aligns with broader human-AI collaboration frameworks, such as Song et al.'s (2024) classification of AI roles (e.g., facilitator, ideator) and the trend toward synthesis-oriented AI that supports creativity and exploration. Despite these advancements, most AI design tools still treat prompt input as a static feature, typically treated as a passive text field. This design approach often lacks structure or guidance, offering limited support for iterative refinement, contextual adaptation or evolving collaboration. Prompts are commonly executed as isolated commands rather than as part of a dynamic dialogue shaped by the user's intent, constraints, or domain knowledge.

3. Research approach

3.1 Research Problem & Objectives

Building upon the theoretical foundations of human-centered AI and prompt engineering (Ye et al., 2023; Zhou, 2023), this research addresses the practical challenges faced by UX/UI designers when integrating large language models (LLMs) into their creative workflows. As discussed in the related works section, AI-driven design tools are increasingly used to support various tasks, aspects, and stages of the design process. These tools offer significant opportunities for accelerating design processes. However, their effectiveness is heavily dependent on the quality of prompts provided by the user. There remains a significant gap in supporting designers to formulate effective prompts in field-specific topics. Existing AI design tools provide limited guidance on prompt creation, leaving designers reliant on trial and error (Takafoli, Li, & Mäkelä, 2024). Furthermore, current research largely focuses on improving LLM outputs through model optimization rather than empowering users with tools for better prompt formulation. This results in missed opportunities to integrate AI meaningfully into design processes. Prompt engineering requires complex reasoning and task-specific knowledge, which many designers do not inherently possess (Ye et al., 2023). Without structured guidance, designers face challenges in articulating design intentions effectively to LLMs, leading to suboptimal outputs and frustration.

Although AI integration in UX design is advancing rapidly, existing systems frequently demonstrate limitations in handling creative tasks and nuanced design problems. Research by Liang, Zhang, and Wang (2023) notes that while many companies have adopted AI tools, users often experience issues related to low output quality, poor contextual understanding, and weak integration into core workflows. Among the available AI tools and large language models like ChatGPT have proven to be the most robust and versatile, capable of supporting a wide range of language-driven design tasks. However, their effective integration into UX practice requires deliberate and context-sensitive implementation. This research responds to these limitations by developing **PromptlyUX**, a Figma plugin that integrates LLM-based prompting assistance directly into the designer's primary workspace. The tool is designed to leverage the strengths of LLMs while mitigating current usability barriers by offering structured, domain-specific prompt templates and workflow-aware guidance.

Moreover, there is limited empirical evaluation of tools that integrate prompt assistance directly into design environments, particularly regarding their effectiveness in improving both prompt quality and user confidence. This thesis aims to bridge this gap by investigating how AI-powered prompt assistance can support designers in crafting effective prompts within their existing workflows. The primary focus is the development and evaluation of PromptlyUX, an AI-augmented plugin designed to guide designers through prompt formulation and refinement. This plugin offers both educational value and practical support, and the study is driven by the following research questions:

3.2 Research Questions

1. Does structured guidance for assisting users to write prompts improve the perceived efficiency of applying AI to UX/UI design tasks?

2. How does prompt assistance impact the perceived usability and cognitive workload of AI tools in the design process?

3. Does structured prompt assistance influence designers' satisfaction with AI integration and their willingness to adopt AI in future workflows?

4. What are the main challenges and benefits experienced by designers when using AI tools with integrated prompting support?

To address these questions, this thesis is divided into two separate parts. The first stage focuses on the design and development of the plugin PromptlyUX. The second stage evaluates the effectiveness of the plugin through a user study involving comparative design tasks, where participants use AI tools both with and without prompt guidance. Quantitative and qualitative measures are used to assess efficiency, usability, cognitive load, and user satisfaction.

4. Methodology

4.1 PromptlyUX

To investigate how prompt assistance can improve the use of large language models (LLMs) in UX/UI design workflows, a custom Figma plugin was developed**.** Figma was selected due to being an industry-standard tool and because all participants involved in the study were already well-acquainted with this software environment. This plugin served not only as a practical tool for designers, but also as a research instrument to explore how structured prompt guidance impacts designers' confidence, efficiency, and overall AI integration. The development was guided by the central hypothesis that integrating prompt scaffolding into the designer's natural working environment would lower the cognitive burden of interacting with AI, improve output quality, and increase adoption willingness.

The plugin was implemented using modular JavaScript and the Figma Plugin API[1], ensuring maintainability and extensibility. It adopts modern UI components consistent with contemporary Figma plugin aesthetics, enabling a visually seamless experience. The system communicates with the OpenAI GPT-4 model via a session-based API key, allowing real-time AI support directly within the plugin interface. The entire source code is publicly available on the author's GitHub repository for full transparency and potential reuse.[2]

The plugin was architecturally designed around a few foundational principles. A key aspect is the contextual integration which ensures designers to seamlessly interact with AI without disrupting their workflow by leaving the Figma environment. Additionally, comprehensive prompting support was implemented to facilitate users in generating, refining, and comprehending prompts effectively. These guiding principles were developed through a combination of existing scholarly literature (Valentine, 2024; Garg, 2024; Fatima, 2024) on prompt engineering and AI adoption barriers in creative disciplines, complemented by insights from preliminary user feedback interviews that identified specific pain points where designers felt disoriented when utilizing Large Language Models without adequate guidance.

[1] https://www.figma.com/plugin-docs/
[2] https://github.com/Dracava/PromptlyUX

Feature 1: Getting Started Survey

To ensure relevant and personalized AI support, the user can choose to begin with a 10-question onboarding survey that captures key project characteristics such as design goals, audience, style preferences and product complexity as can be seen in Figure 2. They then receive a dynamic project overview that can be sent to the AI chat.

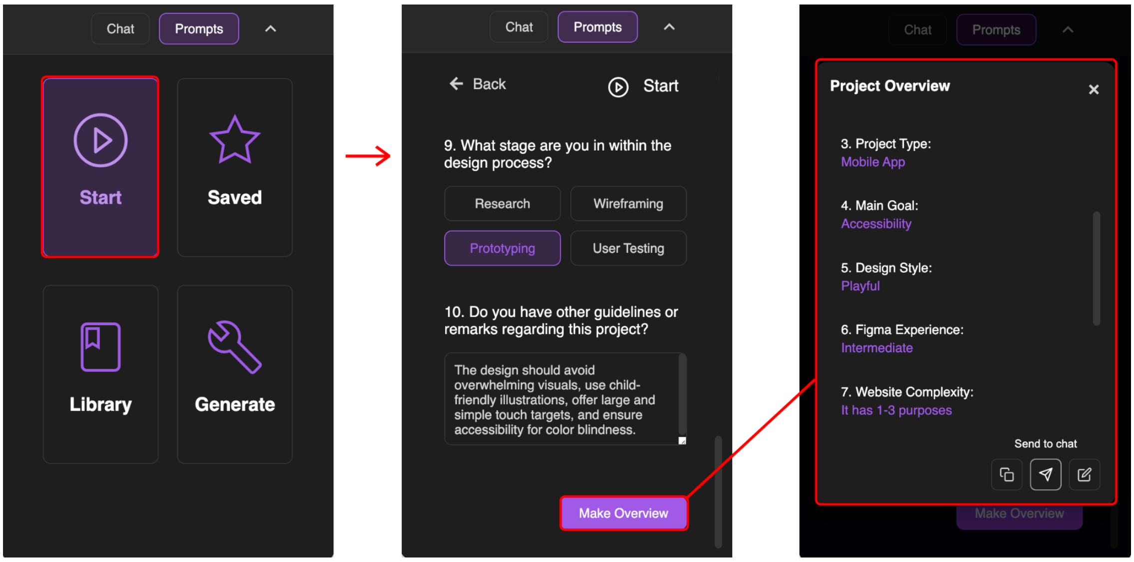


Figure 2. Interface flow of the onboarding survey.

Rather than treating prompting as a blank-slate activity, this structured intake transforms user input into a dynamic project brief that can be sent directly to the AI chat, grounding all subsequent suggestions in a concrete design context. This approach reflects best practices in AI prompting design. Research from the Maastricht University AI Prompt Library (2023) demonstrated that embedding contextual placeholders, such as audience, purpose, and style, improves prompt relevance by 42% and reduces task abandonment by nearly a third. Questions like “What is the main goal of your design?” and “What is your preferred design style?” operationalize this principle, enabling context-aware prompting even for users unfamiliar with prompt engineering conventions. By collecting this data upfront, PromptlyUX reduces ambiguity during AI interaction, one of the most common causes of user frustration and irrelevant output in design support tools (Garg & Rajendran, 2024). This aligns with structured prompting strategies that emphasize constraint-setting and intent clarity (StructuredPrompt, 2024).

Additionally, the onboarding mechanism supports cognitive load reduction by eliminating the need for users to repeat or reframe their project context during each interaction, a factor identified as crucial for maintaining flow and reducing NASA-TLX mental demand scores (Hart & Staveland, 1988). Ultimately, the getting started survey serves a dual purpose: it simplifies the user’s initial setup process while enhancing the quality and precision of the AI's responses. This tightly integrates project context into prompt formulation, establishing a project-aware AI experience that reflects broader shifts toward embedded intelligence in UX workflows. The complete list of questions is provided in Appendix A.

Feature 2: Follow-Up Prompt

To support sustained interaction and reduce conversational dead-ends the plugin integrates smart, clickable "suggestion bubbles" that appear after each AI-generated response. These suggestions offer users contextually relevant follow-up questions, helping them continue the ideation process without needing to think of what to ask next. This mechanism is grounded in the concept of prompt chaining, a technique in which each prompt builds upon the previous one to create a coherent and evolving dialogue with the model (Orq.ai. (2023) For example, after generating a user persona named “Sofia,” the system might ask: “What specific digital marketing trends does Sofia find challenging to keep up with?” (see Figure 3). Clicking this bubble auto-populates the input field, streamlining the continuation of the conversation and reducing cognitive load.

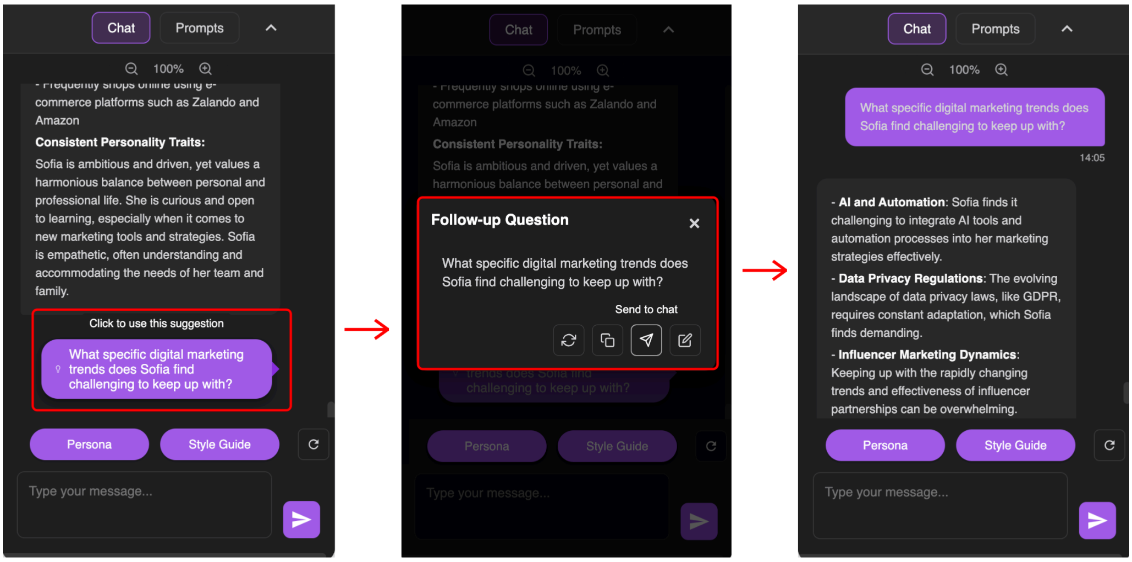


Figure 3. Contextual follow-up prompt suggestions for continued interaction.

Behind this feature are two distinct prompt structures that are critical to the behavior of large language models: the “system prompt” and the “user prompt.” The system prompt defines the assistant’s identity and behavior throughout the session. It is set by the developer and remains stable, establishing foundational rules, tone, and ethical constraints. End users typically do not have direct access to this layer, as it is embedded within the tool’s architecture. However, PromptlyUX allowed for a more tailored approach to system-level behavior. The assistant's persona was designed for UX design contexts by embedding domain-specific instructions and illustrative examples into the system prompt. These guidelines encouraged the AI to behave as a knowledgeable, collaborative UX assistant prioritizing relevance, precision, and design literacy in its suggestions.

The creation of this feature involved considerable experimentation. The final formulation of the prompt that drives follow-up generation was the result of multiple rounds of testing and refinement. This iterative process required balancing specificity and generalizability ensuring the assistant could offer helpful, context-aware suggestions across a range of design topics. This process revealed that including example follow-up questions directly within the system prompt was one of the most effective strategies for producing desirable results. Rather than relying solely on descriptive instructions, the assistant responded more consistently when provided with concrete linguistic models to emulate.

These examples included:

- "Could you elaborate on [part of previous response]?"
- "How would this design pattern impact user engagement?"
- "What metrics would measure this solution's effectiveness?"
- "Which accessibility considerations apply to this component?"

Including such examples helped the AI internalize both the tone and structure of productive follow-up questions, leading to improved continuity and reduced ambiguity in its output. In practice, the plugin uses a layered prompting strategy. The system prompt instructs the AI to act as a specialized AI assistant focused on generating engaging follow-up questions for UX/UI design contexts, including design principles such as: “Prefer ‘how’ and ‘what’ questions,” and “Reference specific design elements when possible.” The user prompt, by contrast, is dynamic and task-specific generated in real time to direct the assistant’s immediate behavior. For example, PromptlyUX uses input such as: “Generate a focused follow-up question about the most recent topic discussed in our conversation.” This dual-layered approach ensures the model maintains a consistent role while responding flexibly to each new conversational turn. The full system and user prompt are located in Appendix A. As Nebuly (2024) explains, this separation between system and user prompts helps LLMs sustain coherent interaction over time. This approach is further informed by prompt chaining and role-conditioning techniques, which have been shown to enhance AI reliability in multi-turn conversations (Zhou et al., 2023; Ye et al., 2023). By constraining the assistant’s behavior through the system prompt while guiding real-time interaction through the user prompt, PromptlyUX reduces common issues like vague or repetitive follow-up questions observed in unstructured AI chats.

From a user experience perspective, this feature also supports cognitive offloading (Hart & Staveland, 1988), allowing users to externalize next-step thinking and focus on higher-level decision-making. It also reflects the participatory prompting model introduced by Sarkar et al. (2023), in which embedded AI cues help users determine when and how to engage with AI assistance effectively. By offering lightweight suggestions rather than directive commands, the follow-up prompt suggestions reinforce PromptlyUX's role as a co-creative partner rather than a prescriptive tool encouraging autonomy while maintaining momentum. This approach helps counteract concerns about creative constraint in structured prompting systems (Knearem et al., 2023) and supports fluid, conversational exploration in UX design workflows.

Feature 3: Dynamic Prompt Suggestion Tabs

Dynamic prompt suggestion tabs appear above the chat input field as can be seen in Figure 4 and offer inspirational prompt proposals based on both the project's context and UX design in general. These suggestions are not static; users can regenerate them to receive fresh, diverse alternatives across different UX topics. The system is designed to inspire exploration and mitigate the challenge of "prompt paralysis" the hesitation users face when unsure how to articulate their needs to an AI assistant.

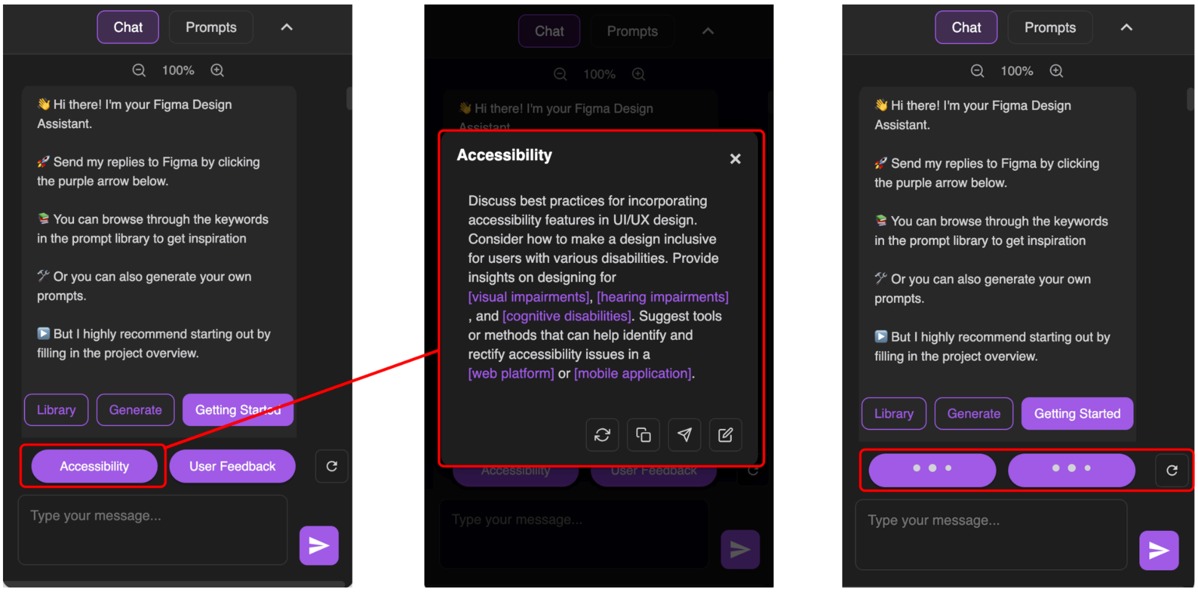


Figure 4. Prompt suggestion tabs offering context-aware, regenerable design prompts.

The system prompt establishes the assistant's role as a prompt suggestion generator and embeds behavioral constraints such as: focus on project context, avoid repetition of recent topics, and exclude action verbs like "create" or "design." This ensures the model provides exploratory, reflective prompts rather than directive commands. For example, it might generate prompts like "How might accessibility needs differ for mobile versus desktop users in this project?" rather than "Design an accessible layout." The user prompt, on the other hand, dynamically updates with each interaction. It pulls in live metadata from the onboarding survey and conversation history, asking the model to produce two diverse prompt suggestions that cover different aspects of the design challenge.

To emphasize critical instructions and shape model behavior, the system and user prompts employ strategic capitalization (e.g., "AVOID," "FOCUS," "IMPORTANT GUIDELINES"). This method leverages the model's sensitivity to visual formatting, as capitalization alters the structure of a sentence and acts as a signal of emphasis. Large language models trained on diverse internet and technical content often associate capitalized terms with importance, urgency, or command. For example, the prompt explicitly instructs: "AVOID suggesting topics similar to the recent conversation topics" and "FOCUS on the PROJECT CONTEXT." These visual cues act as anchor points, guiding the model to attend more closely to key behavioral boundaries during generation.

This structure also operationalizes prompt chaining and constraint-based prompting techniques, which have been shown to reduce repetitive outputs and enhance semantic variety (Zhou et al., 2023; Ye et al., 2023). From a usability standpoint, this feature directly addresses challenges identified by Subramonyam et al. (2022), who found that disconnected tools and lack of contextual continuity were among the most common causes of cognitive friction in AI-assisted workflows. By embedding prompt generation directly in the chat interface and making it project-aware, PromptlyUX preserves spatial and mental continuity two key dimensions in lowering NASA-TLX workload ratings (Hart & Staveland, 1988). This also aligns with design guidance models proposed by Yildirim et al. (2023), who argue that effective AI tools must guide real-time decision-making and offer contextualized support across the design lifecycle. PromptlyUX meets these criteria by presenting prompt suggestions that are not only tailored to the user's current task but also evolve with the workflow. Additionally, the dynamic prompt tabs embody the principles of cognitive scaffolding (Interaction Design Foundation, n.d.) and participatory prompting (Sarkar et al., 2023), enabling users to remain in control of prompt direction while being nudged toward new lines of inquiry. This balance is especially important for maintaining creative momentum without drifting into homogenized or overly guided output, an issue described as the "pluralism paradox" in structured AI support systems (Knearem et al., 2023). In short, these tabs make prompting feel more like ideation and less like coding. They create a lightweight, low-pressure entry point into structured AI dialogue, one that adapts in real time, supports divergent thinking, and evolves with the user's design process.

Feature 4: Prompt Library

The prompt library consists of a curated collection of prewritten, editable prompt examples organized around core UX themes and stages of the Design Thinking Process: Empathize, Ideation, Prototyping, Testing, and Accessibility. These prompts are accessible via collapsible dropdown menus and serve as inspiration and guidance for users who may not know how to structure effective prompts themselves (see Figure 5). Each prompt is intentionally crafted to reflect common UX design activities. For instance:

- "Create a detailed user persona for [product/service] that includes demographic information, behaviors, goals, frustrations, and motivations…"
- "Help me develop a comprehensive user journey map for [specific user persona] interacting with [product/service/process]…"
- "Define a precise target audience for [product/service/content]… including segments, media habits, and behavioral patterns…"

These examples go beyond surface-level templates, they embed UX-specific terminology, assume real-world design goals, and anticipate how users will adapt them. This level of specificity lowers the barrier to entry for prompting by showing how to frame AI queries effectively. From a theoretical standpoint, the prompt library supports cognitive scaffolding (Interaction Design Foundation, n.d.), helping users reduce the mental effort involved in prompt formulation. This is especially valuable for beginners or those new to AI-supported workflows. As Garg & Rajendran (2024) note, editable prompt templates can significantly improve task relevance and reduce user frustration, particularly when they mirror the structure of real-world use cases.

To ensure the relevance and adaptability of these prompts, an iterative refinement process was employed, which was inspired by best practices in prompt design (Latitude, 2023). Prompts were evaluated and adjusted based on their clarity, contextual alignment, and ability to generate useful outputs within varied design scenarios. This cyclical refinement approach testing, observing model behavior, and rephrasing accordingly helped develop prompts that were instructive and useful applicable a wide range of UX tasks.

Moreover, these prewritten prompts function as prompt literacy tools, teaching users what makes a prompt actionable and specific. By giving them strong starting points, the tool encourages iterative experimentation users can regenerate, adapt, and refine prompts over time. This supports the kind of prompt fluency necessary for more advanced AI interaction, again aligning with findings from the Maastricht AI Prompt Library (2023), which showed that example-based prompting improved both confidence and task accuracy. The prompt library also aligns with the design philosophy of divergent thinking, where tools serve as creative scaffolds rather than deterministic solutions (Khan et al., 2025). By offering users multiple prompts across categories and encouraging exploration across tasks like behavioral analysis, accessibility planning, and audience segmentation the feature promotes idea expansion and cross-stage thinking in UX workflows. The library functions as a dynamic ideation tool rather than a fixed resource. It connects beginners with expert-level prompting capabilities, offering both organized templates and creative freedom. Throughout this process it remains grounded in UX terminology and contextual understanding.

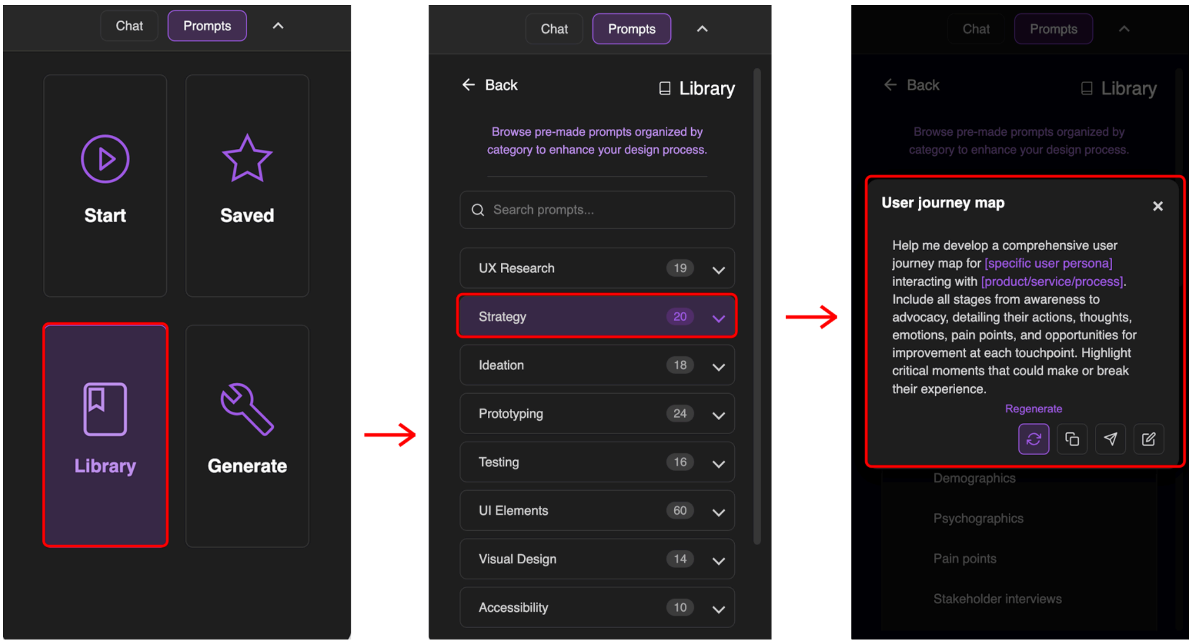


Figure 5. Prompt library organized by UX topics with editable prompt examples.

Feature 5: Generate Prompts

The generate section in the plugin allows designers to type in a freeform topic such as "buttons," "navigation," or "accessibility" and receive three optimized prompt suggestions related to that topic as can be seen in Figure 6.

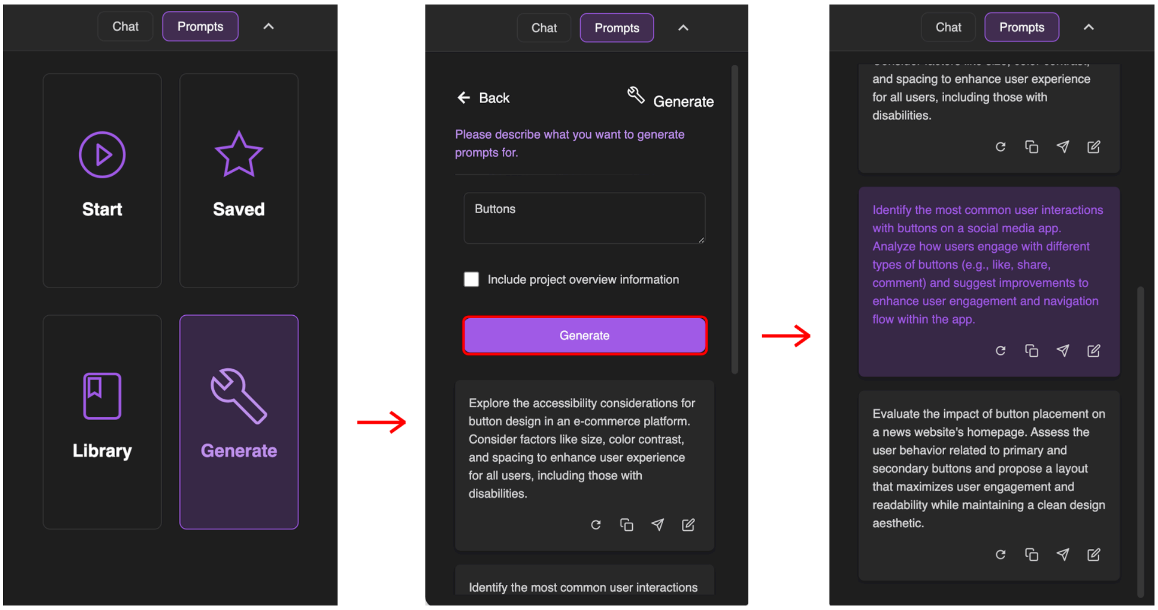


Figure 6. Custom prompt generation based on user-defined themes with optional project context.

Suggestions are generated in real-time and automatically tailored to reflect the user's project context, based on their onboarding responses. This makes the generate feature a fast and flexible tool for bridging specific interests with AI-guided ideation, without requiring users to know how to construct effective prompts themselves. The underlying logic is again driven by a two-tier prompt structure. Similarly to the other prompting features the system prompt defines the assistant's behavior, however this time it includes: to return concise, usable prompts without formatting clutter like titles or quotation marks. It instructs the model to refer to bracketed inputs such as [topic], [user group], or [notes], and to avoid verbs that imply the AI will "design" or "develop" solutions, reinforcing its role as an assistive tool, not an autonomous creator. The user prompt then passes in the specific topic entered by the designer, requesting three distinct prompts and injecting the user's project overview for contextual grounding. This setup mirrors the logic of parameterized prompting as described in the Structured Prompt Notation (SPN) framework (StructuredPrompt, 2024).

By dynamically combining fixed system-level rules with flexible user inputs, the model generates outputs that are both coherent and relevant to the current design scope. It also follows best practices in prompt engineering for UX support tools, where specificity, tone, and question framing are carefully optimized to encourage meaningful AI responses (Zhou et al., 2023; Ye et al., 2023). From a user experience perspective, this feature supports divergent thinking by surfacing multiple angles on a single topic. A user asking about "buttons," for example, might receive one prompt related to accessibility, another on visual hierarchy, and a third focused on microinteractions. This variety helps designers expand their inquiry without being overwhelmed or having to manually phrase follow-ups, an issue frequently observed in novice AI users (Garg & Rajendran, 2024). Moreover, it serves as a low-friction ideation tool, reducing the time spent crafting prompts while still offering high-relevance suggestions. This aligns with the goals of prompt literacy and fluency, giving users repeatable examples of how to engage LLMs effectively. It also supports cognitive alignment ensuring that the AI's output structure mirrors the user's design thinking process and mental framing, a factor shown to increase usability and trust in AI assistants (Al Haque et al., 2025). By building on project context the feature supports more nuanced AI interaction and avoids overly generic outputs. It combines the speed of keyword-based search with the depth of structured prompting, all while remaining anchored in the user's evolving project context supporting both efficiency and creativity in UX workflows.

4.2 Experiment

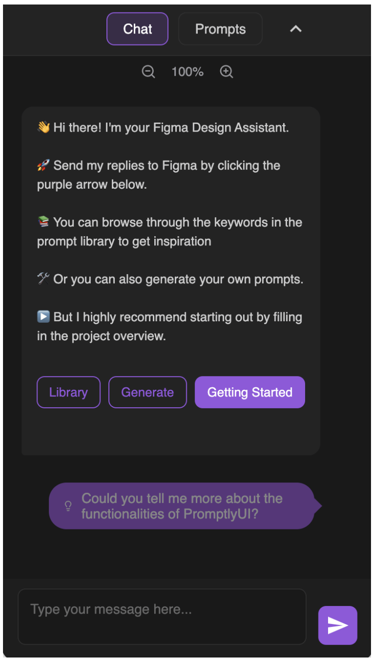
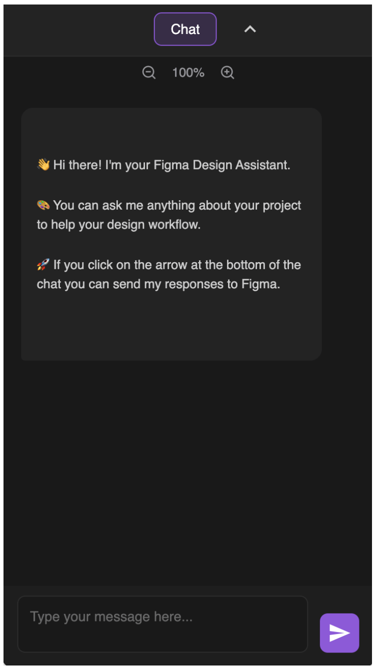
	Group A (Experiment)	**Group B (Control)**
		
Figma Integration	Yes	Yes
AI Chat Access	Yes	Yes
Prompt Tabs	Yes	No
Getting Started Survey	Yes	No
Prompt Library	Yes	No
Context prompts	Yes	No
Follow-up prompts	Yes	No

Table 1. Feature comparison between Group A and Group B.

The second phase of this thesis was an experiment to evaluate the effectiveness of the plugin in real-world UX/UI workflows. The experiment aimed to answer core research questions related to AI-assisted prompting in design: how designers interact with a prompt-enhancing tool, and how such tools influence their productivity, trust in AI, and overall design experience. The plugin's dual structure (Chat vs Prompts) enabled a controlled comparison during this research phase. One group of participants used PromptlyUX with full prompt guidance (experimental group), while the control group used a stripped-down freeform AI chat without any form of prompt assistance. The primary objective was to determine whether PromptlyUX's features improved prompt quality, reduced cognitive load, and helped integrate AI more naturally into the design process. Table 1 summarizes the differences in features for both groups.

Participants

The study included 23 participants, all with backgrounds in UX/UI design and proficiency in Figma. They were recruited through purposive and convenience sampling strategies, including targeted messages to (former) students from a User Experience Design bachelor program, announcements in university-related class group chats, and a public call via social media announcements. Participants were randomly assigned to either Group A (experimental) or Group B (control).

Test

The testing was conducted remotely rather than in a controlled laboratory environment. This approach allowed participants to work on their own personal devices within familiar digital settings replicating their typical design workflows. Each participant had the Figma app pre-installed on their device and the PromptlyUX plugin was shared as a ZIP file, which they could easily load into their existing Figma environment. This setup made sure that participants could use their own workspace configurations including preferred settings, keyboard shortcuts, and other plugins they regularly rely on. Additionally, participants were able to choose their own location which enhanced personal comfort and reduced other external stressors. These conditions were more representative of real-world UX design contexts. Participants were not informed of the two different versions of the plugin and were therefore unable to identify which experimental group they belonged to. All participants received the same core materials and followed a standardized testing process. There was a Figma design project page with a link to the survey, an instruction how to install the plugin and the (clickable) design brief.

Prior to the testing session, all participants completed a pre-survey designed to collect demographic and background information relevant to the study. The purpose of this survey was to establish the diversity of participant profiles and assess their familiarity with AI tools and UX/UI workflows, thereby helping contextualize their performance and feedback later on.

The main test phase the participants included a design challenge which was given through a one-paged brief and included the following:

> **“Objective**: Design a health dashboard application through Figma.
> Prototype or wireframe at least 1 page, you can make it as elaborate as you want. Other plugins are permitted, but use the PromptlyUX plugin as much as possible to assist with your design workflow.
>
> **Target group**: **Children with Type 1 Diabetes and their caregivers**
> These are children (ages 6–14) managing a complex chronic condition that requires continuous monitoring and adjustment throughout their daily lives. If needed, use the AI tool to generate insights about this group.
>
> **Imagine this platform serves as a digital health hub** where these children and their caregivers can:
>
> - Monitor blood glucose levels, insulin dosing, and carbohydrate intake in age-appropriate ways
> - Track physical activity and its effects on blood sugar levels
> - Connect with healthcare providers and school nurses to share critical health data”

This particular target group and challenge was chosen because it involved a target group that was specialized enough to ensure participants had limited prior knowledge. As a result, the scenario created a need to research the topic to inquire a more contextual understanding, making it an ideal case to assess whether AI assistance could effectively support designers in acquiring domain-specific insights. The dashboard format also introduced a high level of complexity, requiring participants to consider diverse visual elements such as color-coding systems, health data hierarchies, and accessibility features. Unlike more conventional domains like e-commerce applications or portfolio websites, where well-established UI patterns and industry standard templates exist. This open-endedness allowed for greater creative exploration in less standardized contexts. The full brief is available in Appendix B for reference.

Further, the brief requested three deliverables to be done within a timeframe of half an hour, each related to specific stages of the Design Thinking Process (Yudhanto et al., 2022) to evaluate how the AI assistance performs across a broad spectrum of UX tasks. The first deliverable was a user persona, aligned with the empathize and define phases by encouraging participants to research and articulate user needs, frustrations, goals, and behavior patterns. This step established the challenge's foundation in human-centered thinking and tested the plugin’s ability to support early-stage ideation. The second deliverable, a style guide, corresponded with the ideate and prototype stages, asking participants to define consistent visual principles such as color, typography, and iconography, suited to both medical accuracy and child-friendly interaction. This tested the capability to support systematic visual planning. Finally, the one-page prototype or wireframe brought participants into the prototype and test phases, requiring them to apply their insights in a functional interface while considering usability and interaction flow. By combining these deliverables into one cohesive design challenge, the study assessed whether integrated prompt assistance could enhance designer performance across multiple points in the UX workflow, thus evaluating the plugin’s value as a holistic design support tool.

By grounding the assignment in a realistic, socially relevant scenario and requiring practical deliverables, the design task enabled a meaningful and task-relevant evaluation of the tool's usefulness and usability.

After the testing a post-test evaluation was conducted to gather both quantitative and qualitative data on participants' experiences with the PromptlyUX plugin. A mixed-methods approach was used by combining structured surveys and open-ended interviews. This methodological design was chosen to ensure triangulation across data sources and to address the full scope of the research questions.

To measure perceived usability, the study utilized the standardized System Usability Scale (SUS) which asked participants to rate ten usability-related statements on a 5-point Likert scale ranging from "Strongly Disagree", "Neutral" to "Strongly Agree." These responses provided insight into participants' overall ease of use, confidence, and satisfaction with the plugin interface, directly informing research question number 2 regarding usability. To evaluate cognitive workload, participants completed the NASA Task Load Index (NASA-TLX), which assessed mental demand, physical effort, time pressure, performance, effort, and frustration across a 0-5 scale ranging from "Very Low", "Moderate" to "Very High." These metrics were used to evaluate the impact of prompt assistance on cognitive burden. Participants also rated their satisfaction with various aspects of AI integration using a 5-point scale, including the quality, relevance, and speed of AI-generated suggestions, as well as the overall AI experience. These metrics contributed to answering research question 3, which explored the influence of structured prompt assistance on satisfaction and future adoption intent. To further capture adoption likelihood, participants were asked whether they would use AI in their workflow again, selecting from "Yes," "No," or "Maybe." For participants in the experimental group (Group A), an additional set of Likert-scale items assessed the perceived effectiveness of PromptlyUX's prompting features, including the prompt library, custom prompt generation, project overview, and follow-up suggestions. This provided deeper insight into how specific design features contributed to perceived utility, efficiency, and confidence, thereby addressing both research questions 1 and 3. Appendix C contains the full version of both the pre-test demographical questions and the post-test evaluations.

Finally, to address research question 4 regarding perceived benefits and challenges participants were invited to provide open-ended comments about their experience. These included prompts such as "What was the most helpful aspect of the AI system?" and "What was the most challenging?" Group B participants were also asked to reflect on how the lack of prompting assistance influenced their design process. This multi-layered post-test evaluation enabled a nuanced understanding of how structured prompting impacts AI-augmented design workflows. By combining standard usability and workload metrics with adoption indicators and qualitative feedback, the methodology supported an elaborate evaluation of PromptlyUX across functional, cognitive, and experiential dimensions.

5. Results

5.1 Participants

The study involved 23 participants with diverse backgrounds in design and varying degrees of familiarity with AI tools. In terms of design experience, the majority of participants (n=16) were at an intermediate level, with approximately 2 to 4 years of experience in the field. A smaller group (n=5) had advanced expertise, having worked in design for more than five years, while two participants were classified as beginners, each with less than one year of experience. Regarding the use of AI in design workflows such as tools like ChatGPT or Midjourney most participants (n=18) indicated prior experience with these technologies, whereas five participants reported having no experience with AI tools. Despite this variation, attitudes toward AI were largely positive. Nineteen participants expressed a favorable view: fifteen were somewhat positive, and four were very positive. Only four participants demonstrated skepticism, three somewhat skeptical and one very skeptical. Demographically, the participant group was predominantly female (n=15), with a smaller number of male participants (n=8). The age distribution ranged primarily between 20 and 29 years, with 21 participants falling into this bracket, suggesting a sample composed mainly of young adults, typical of design students or early-career professionals. Only two participants were aged between 30 and 39. This age range, combined with the high proportion of intermediate-level designers, suggests that most participants were still relatively early in their professional design journeys but had accumulated enough experience to engage meaningfully with both design tasks and AI-assisted tools.

5.2 Survey

The System Usability Scale (SUS) scores were calculated by first converting each participant’s responses according to standard SUS scoring rules. For the positively worded items (questions 1, 3, 5, 7, and 9) the score contribution was determined by subtracting 1 from the original Likert-scale response. For the negatively worded items (questions 2, 4, 6, 8, and 10), the contribution was calculated by subtracting the response from 5. This process resulted in a score from 0 to 4 for each item, which were then summed and multiplied by 2.5 to produce a total SUS score out of 100 for each participant. The mean SUS score for Group A was 78.86, indicating a high level of perceived usability. In contrast, Group B reported a lower average score of 67.05. This finding is further illustrated in Figure 17, which presents a radar chart mapping the average response values across all ten SUS dimensions. Each axis of the chart corresponds to a usability attribute (e.g., "Easy to Use", "Need Support", "Confident"), with higher scores indicating more favorable perceptions. Group A consistently rated the plugin more positively across nearly all categories, particularly in areas such as "Learn Quickly", "Cumbersome", and "Use Frequently". The more compact shape of Group B’s polygon represents the less positive responses and more variable perception of the system’s usability.

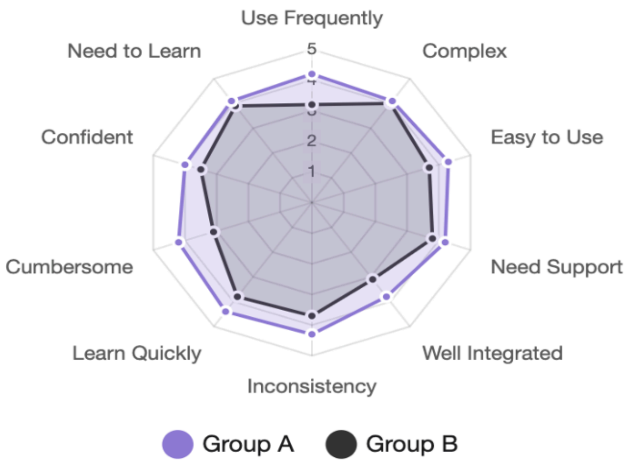


Figure 17. Average Ratings on System Usability Scale (SUS)

In addition to usability perceptions, participants' subjective workload was assessed using the NASA Task Load Index (NASA-TLX), which measures six dimensions: mental demand, physical demand, temporal demand, performance, effort, and frustration. The responses, which originally recorded using qualitative labels such as "Low" and "High," were converted to numerical values on a 0-100 scale to enable quantitative comparison. Group A reported noticeably lower frustration (M = 18.18) and rated their task performance higher (M = 70.45) than Group B, which indicated substantially higher frustration (M = 50.00) and lower perceived success (M = 50.00). While physical demand was slightly higher for Group A (M = 27.27), Group B reported greater levels of mental demand (M = 56.82) and temporal pressure (M = 50.00). These patterns are visually summarized in Figure 18, where the broader spread of Group B's profile. Particularly in frustration, mental demand, and temporal demand, indicating that participants in this group more frequently rated these aspects as high. Group A's responses are more concentrated in the lower to moderate range, with higher ratings observed primarily for perceived performance.

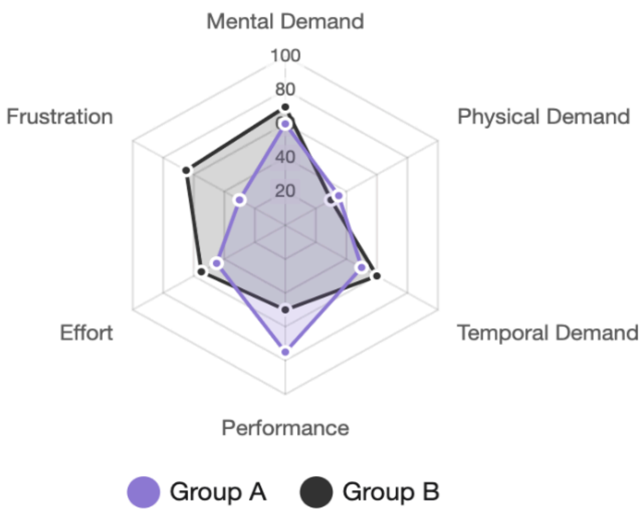


Figure 18. Average Ratings on NASA Task Load Index (NASA-TLX)

Figure 19 illustrates that, on average, participants from both Group A and Group B held a positive attitude toward AI prior to testing. Following the testing the responses show that the majority of Group A participants expressed a willingness to use AI again, whereas responses from Group B were more varied, selecting both 'Maybe' and 'Yes'. Further, the figure shows a difference in satisfaction levels between the two groups, with only participants from group B indicating dissatisfaction. The final graph in the same figure presents the self-reported task completion times for both groups. The majority of Group A participants indicated that tasks were completed "Much faster," while responses from Group B were more distributed.

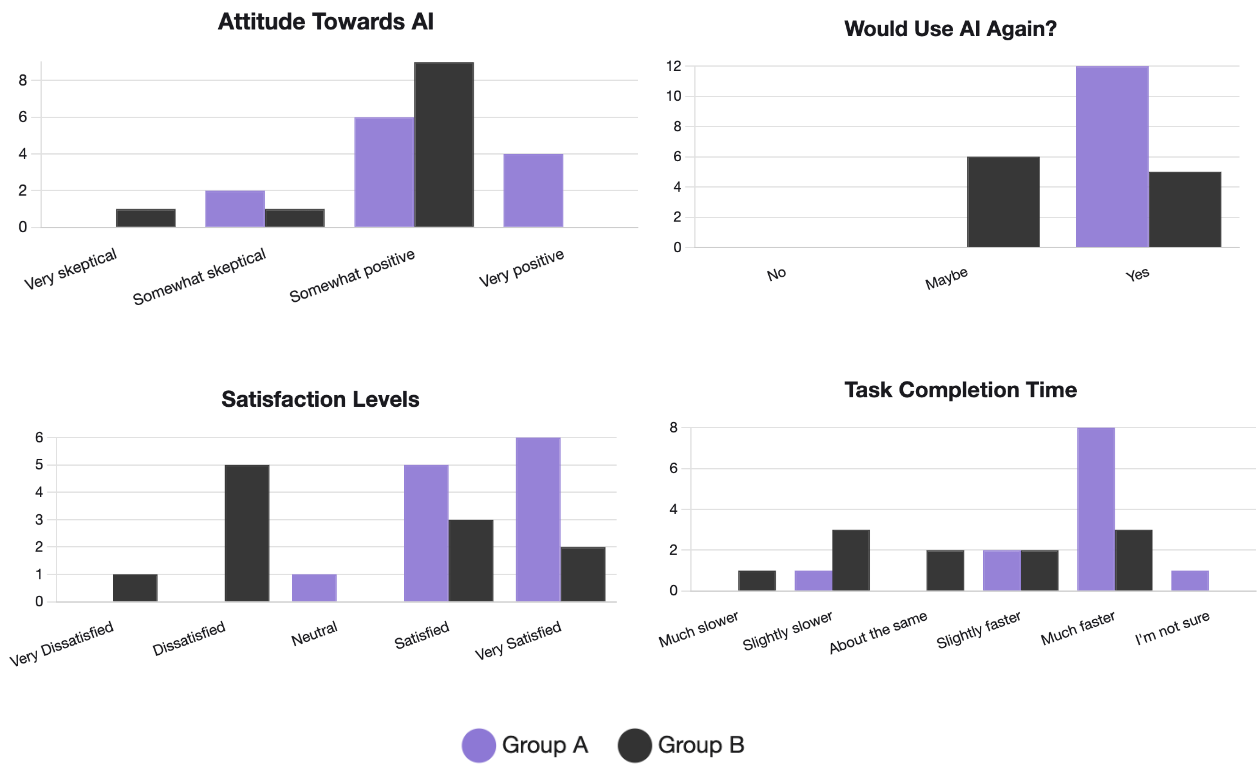


Figure 19. Participant Feedback on PromptlyUX

Quantitatively, the impressions reported by participants were supported by statistically analyzed survey metrics. For each key category: usability, satisfaction, and intention to reuse AI tools we calculated the average score, known as the mean (abbreviated as M), as well as the standard deviation (SD), which indicates how spread out the responses were. A lower standard deviation means that most participants gave similar ratings, while a higher standard deviation suggests more varied responses. Satisfaction with the AI integration was notably higher among participants in Group A, who used the PromptlyUX plugin with prompting assistance. Their average (mean) satisfaction score was M = 4.42 with a standard deviation of SD = 0.67, indicating not only a high level of satisfaction but also fairly consistent responses across the group. In comparison, Group B participants had a much lower average satisfaction score of M = 3.00 (SD = 1.41), reflecting more neutral and varied reactions. A statistical test (independent samples t-test) confirmed that this difference is statistically significant, t(approx) = 3.03, p = .009, meaning it is unlikely to be due to chance. Similarly, when asked whether they would use AI tools again in their future design workflows, participants in Group A gave uniformly positive responses, with a perfect average score of M

= 3.00 (SD = 0.00) meaning every individual answered “Yes.” In contrast, Group B participants were more uncertain or hesitant, averaging M = 2.45 (SD = 0.52), with several answering “Maybe.” This difference was also statistically significant, t(approx) = 3.46, p = .006, highlighting that exposure to prompting assistance not only affected participants' current experience but also shaped their future intentions and openness to integrating AI into their design practices. Although the usability ratings were slightly higher for Group A (M = 2.17, SD = 1.53) than for Group B (M = 1.73, SD = 0.90), this difference did not reach statistical significance (t(approx) = 0.85, p = .408). A summary of the statistical comparisons between Group A and Group B is presented in Table 2, including mean scores, standard deviations, t-values, p-values, and significance levels for each measured category. In practical terms this means that while users with prompting assistance may have perceived the plugin as somewhat easier to use, the evidence is not strong enough to conclude that the prompting feature alone was responsible for this difference.

Category	Group A Mean (SD)	Group B Mean (SD)	t-value	p-value	Significant (p < .05)
Usability	2.17 (1.53)	1.73 (0.90)	0,85	0,408	No
Satisfaction	4.42 (0.67)	3.00 (1.41)	3,03	0,009	Yes
Reuse Intent	3.00 (0.00)	2.45 (0.52)	3,46	0,006	Yes

Table 2. Statistical Comparison of Survey Results Between Group A and Group B

5.3 Interviews

Beyond the survey responses, semi-structured interviews revealed a range of participant reflections on the plugin’s strengths and areas for improvement. Several participants in Group A (PromptlyUX with prompting assistance) appreciated the time-saving benefits and ease of use, frequently highlighting the plugin’s integration into Figma as a key advantage. Participants noted that the tool helped reduce their cognitive workload and clarified their design direction, particularly through context-aware prompt suggestions. The in-chat prompting assistance and persona-specific responses were seen as especially useful for accelerating ideation and overcoming creative blocks. Nonetheless, some Group A users suggested enhancements to increase flexibility and clarity. Two participants proposed a more customizable “Start” screen to better adapt to different workflows, while others mentioned the need for clearer onboarding or better indication of where prompt content was coming from. A few participants also expressed concerns about limitations in the AI’s creative output, preferring to maintain control over final decisions to avoid “losing independence,” as one participant phrased it. In contrast, Group B participants, who used the baseline AI chat interface, often struggled with prompt formulation and reported receiving less relevant or repetitive responses. Several described the tool as more time-consuming or less intuitive compared to what they expected. Suggestions from this group centered around wanting more contextual guidance, a built-in prompt library, or clearer segmentation of outputs to align better with the design task stages.

6. Discussion

This section interprets the findings of the PromptlyUX evaluation and situates them within the broader context of AI-assisted UX/UI design and prompt engineering. It revisits the core research questions, explores the implications of structured prompting, and highlights how integrated prompting tools reshape designers' workflows and attitudes toward AI adoption. The study design employed a mixed-methods approach, combining structured surveys (e.g., SUS, NASA-TLX), Likert-based evaluations, and open-ended interviews. This triangulated methodology provided a thorough understanding of the prompting assistance impact, particularly in measuring dimensions like satisfaction, adoption intent, and perceived efficiency.

The results demonstrate that embedding structured prompting support such as onboarding surveys, follow-up suggestions, and contextual prompt generation significantly enhanced both the user experience and the long-term adoption potential of AI tools. These findings directly address research question 1, which asked whether structured guidance improves the perceived efficiency of applying AI in UX/UI design tasks. PromptlyUX users (Group A) reported smoother, more intuitive interactions with large language models (LLMs), transforming what is often a trial-and-error process into a more guided and confidence-building experience. This aligns with existing research that emphasizes the value of structured prompting in reducing cognitive load (Ye et al., 2023; Garg & Rajendran, 2024), enhancing trust (Sarkar et al., 2023) and supports ideation processes in design workflows (Khan et al., 2025).

One of the most notable outcomes was the reduction in cognitive workload, answering a core aspect of research question 2, which explored how prompting assistance affects perceived usability and cognitive effort. NASA-TLX scores indicated that Group A participants experienced substantially lower mental demand ($M = 40.91$ vs. 56.82), temporal demand ($M = 34.09$ vs. 50.00), and frustration ($M = 18.18$ vs. 50.00) compared to Group B. They also reported higher perceived performance ($M = 70.45$ vs. 50.00), suggesting PromptlyUX helped streamline the user experience and minimizing uncertainty in prompt formulation. This supports findings from prior research (e.g., Subramonyam et al., 2022) which show that reducing ambiguity through structured interaction helps users better articulate complex design problems. PromptlyUX's ten-question onboarding survey, dynamic prompt tabs, and follow-up suggestions acted as cognitive scaffolding (Interaction Design Foundation, n.d.), providing a clearer starting point and reducing decision fatigue. These results reinforce the view of Ye et al. (2023) and Zhou et al. (2023) that prompt engineering often involves navigating unclear boundaries, making any form of guidance valuable even for experienced designers.

The usability and trust benefits of the assistance were also evident in the higher System Usability Scale (SUS) scores with Group A achieving an average score of 78.86, compared to 67.05 for Group B. This reinforces the core concerns addressed in research question 2. Although the difference between these means was not statistically significant ($p = .408$), it remains meaningful from a usability perspective. SUS scores are not percentages but are calculated on a scale from 0 to 100, based on users’ responses to a ten-item questionnaire that alternates between positively and negatively worded items. Each response is converted into a score from 0 to 4, then summed and multiplied by 2.5 to construct the final score.

According to Bangor et al. (2009), a SUS score of 68 is generally regarded as the average benchmark across products and industries. Scores above this threshold indicate above-average usability, while scores below suggest room for improvement. Group A's score of 78.86 falls well within the "good to excellent" range, suggesting that users found the plugin highly usable and effective. In contrast, Group B's score of 67.05 hovers just below the benchmark, placing it in a marginal or "okay" usability category. While not poor, this score implies that the user experience was more variable and less consistently satisfying.

It is also possible that the observed results were influenced by the novelty effect, where participants' perceptions are temporarily elevated due to the excitement of engaging with a new or unfamiliar tool (Norman, Miller, & Henderson, 1995). This psychological bias may have led users to evaluate the plugin more favorably simply because it felt innovative, especially in the absence of long-term usage. While both groups may have been subject to this effect, it is noteworthy that Group A's experience still outperformed Group B's across key metrics, suggesting that beyond the initial appeal, the structured prompting support may have delivered a genuinely more effective and satisfying user experience. Detailed radar plots (Figure 17) illustrate that Group A consistently rated the plugin more positively across core usability attributes, especially in areas like ease of learning, frequency of use, and overall smoothness of interaction. These trends point to a general sense that the assistance helped users feel more confident, competent, and comfortable when engaging with AI tools. These findings align with earlier studies on CLAICA (Kernan Freire et al., 2023) and participatory prompting (Sarkar et al., 2023), which highlight the importance of embedded guidance and transparency in fostering user satisfaction. By embedding prompting directly into the Figma interface, the plugin minimized context-switching and supported continuity, effectively reducing the "gulf of execution" (Subramonyam et al., 2022) and making AI feel like an integrated collaborator within the design process.

PromptlyUX also addressed what has been described as the "prompt literacy gap" (Zamfirescu-Pereira et al., 2023), which is the disconnect between what designers intend and what LLMs need to generate relevant outputs. This directly relates to research question 4, which sought to understand the benefits and challenges designers experience when using prompting assistance. Participants valued how the plugin provided well-structured, domain-specific suggestions that mirrored UX terminology and practices. This empowered even novice users to produce high-quality prompts without needing prior expertise in AI interaction. Structured prompt libraries, editable templates, and dynamic suggestions made the system feel both supportive and adaptable, contributing to overall satisfaction and usability. Beyond immediate task support, the statistically significant difference in reuse intent ($p = .006$) between the two groups directly informs research question 3, which explored whether prompting assistance influences designers' satisfaction with AI integration and willingness to adopt it in future workflows.

Group A participants demonstrated greater openness to continuing AI use, reflecting a shift in long-term attitudes. This supports the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), which identifies perceived usefulness and ease of use as key drivers of adoption, and echoes findings from Zhu et al. (2024), who show that domain-specific guidance enhances AI acceptance in professional settings. However, it is worth noting that participants in Group A already expressed slightly higher enthusiasm toward AI tools prior to testing, as indicated in the pre-task survey responses.

This pre-existing positive disposition may have influenced their receptiveness to the plugin's features and shaped their post-test evaluations. As such, this enthusiasm could be a confounding factor, and should be acknowledged as a limitation when interpreting differences in adoption intent between the groups. Future studies may benefit from balancing groups based on baseline attitudes or incorporating attitudinal controls to isolate the effect of prompting assistance more clearly.

Additionally, PromptlyUX's role as a "creative collaborator" (Khan et al., 2025) was clearly observed. The tool's ability to generate multiple, context-aware prompts helped participants avoid design fixation and encouraged exploration, strengthening their divergent thinking capabilities. Unlike template-driven systems that risk homogenization (Knearem et al., 2023), PromptlyUX maintained creative momentum while keeping users in control of the design process. Importantly, this study demonstrates that effective prompt engineering is not a one-size-fits-all solution. It is deeply contextual and shaped by domain expertise, project stage, user goals, and interface constraints. PromptlyUX's ability to dynamically adapt suggestions based on project metadata, design goals, and style preferences exemplifies how AI tools can evolve from being generic assistants to domain-sensitive collaborators. This design model supports calls from Huang (2024) and Liang et al. (2023) to integrate AI tools more meaningfully into creative environments.

In summary, PromptlyUX enhanced satisfaction and future adoption intent, while also showing a trend toward improved usability. Beyond these outcomes, the tool supported deeper shifts in design cognition, creative efficiency, and trust in AI systems. These findings reinforce the emerging perspective that prompting is not just a technical input but a design dialogue one that must be supported, structured, and personalized to unlock the full potential of AI in UX workflows.

7. Conclusion

7.1 Summary of Findings

This thesis explored the role of AI-assisted prompting tools in UX/UI design, specifically focusing on the impact of PromptlyUX, the Figma plugin designed to support prompt creation for large language models (LLMs). The study demonstrated that structured prompt guidance significantly improves designers' interactions with AI tools across multiple dimensions, with implications that extend beyond immediate usability to the broader evolution of human-AI collaboration in creative fields. The results revealed compelling evidence that structured prompting assistance reduces the cognitive burden experienced by designers when working with AI. Participants using PromptlyUX (Group A) consistently reported lower mental demand, frustration, and temporal pressure compared to the control group, as measured by the NASA Task Load Index (NASA-TLX). Group A also rated their task performance higher and experienced less variability in workload perception. These findings suggest that the cognitive effort required to formulate effective AI queries is substantially reduced when appropriate prompting infrastructure is provided. This reduction in cognitive load allows designers to focus more on creative decision-making rather than struggling with how to communicate their intentions to AI systems.

In terms of usability, participants with access to PromptlyUX reported an average System Usability Scale (SUS) score of 78.86, placing their experience well within the “good to excellent” range. In contrast, the control group (Group B) averaged 67.05, a score closer to the industry benchmark but suggestive of more mixed experiences. Although the difference between groups was not statistically significant, it reflects a meaningful shift in perceived ease of use, clarity, and confidence, especially considering that SUS scores are widely recognized as robust indicators of overall system usability. These usability and workload findings work in tandem to demonstrate that structured prompting not only lightens the mental load but also enhances the perceived quality of the interaction itself. The data further showed a statistically significant improvement in user satisfaction among those with access to prompting features. Group A participants rated their satisfaction with AI integration markedly higher ($M = 4.42$) than those in the control group ($M = 3.00$, $p = .009$). This substantial difference indicates that structured prompting creates a more positive and productive experience, potentially addressing common frustrations that designers typically encounter when working with AI tools in creative contexts.

Perhaps most notably, all participants in Group A (100%) indicated willingness to continue using AI in their future design workflows, selecting "Yes" when asked about reuse intent. This stands in stark contrast to the mixed responses received from Group B, where several participants selected "Maybe" or "No." This finding is particularly significant as it demonstrates that well-designed prompt assistance not only improves immediate user experience but strengthens long-term adoption potential, a crucial factor for the sustainable integration of AI into professional design practices.

The qualitative feedback revealed that specific features of PromptlyUX were instrumental in bridging what researchers have termed the "prompt literacy gap." Participants highlighted how the onboarding survey helped establish project context, the prompt library provided structured starting points, and follow-up suggestions maintained conversational momentum. These elements collectively enabled designers to articulate their creative intentions more effectively to AI systems, resulting in more relevant and useful outputs.These findings contribute significantly to the evolving understanding of human-AI collaboration in creative contexts. By developing and evaluating a purpose-built tool for UX/UI designers, the study demonstrates how AI integration can move beyond generic applications toward domain-specific support that respects existing workflows and professional practices. PromptlyUX exemplifies a paradigm shift in AI tool development from treating prompting as a user responsibility to recognizing it as a core design challenge. This perspective repositions prompt engineering not merely as a technical skill but as a crucial interface between human creativity and machine capabilities, one that requires thoughtful scaffolding to maximize value and minimize friction.

The results suggest that prompt-enhanced AI tools could significantly accelerate the integration of AI into design practices, reducing barriers to adoption while empowering designers to maintain creative control. This balance addresses concerns about AI homogenization in design outputs by positioning AI as a collaborative partner rather than an autonomous creator. By reducing barriers to effective communication with AI, PromptlyUX demonstrates how thoughtful interface design can reshape the relationship between designers and emerging technologies, fundamentally transforming how designers perceive and integrate AI into their creative processes.

7.2 Limitations

Despite the promising results, this research has several limitations that should be acknowledged when interpreting its findings and considering its broader applicability. The study's sample size and composition present notable constraints on generalizability. With 23 participants involved in the research, the statistical power is adequate for identifying major effects but may not capture more subtle influences or edge cases in designer-AI interaction. Furthermore, the participant pool was predominantly composed of younger designers between 20-29 years of age with intermediate experience levels. This demographic concentration, while representative of many early-career designers, does not fully capture the perspectives of senior design professionals who might approach AI tools with different expectations, work habits, and levels of technical adaptability. These experienced designers could potentially reveal different patterns of AI interaction and acceptance that were not observed in the current sample.

Time constraints imposed by the experimental design also limit the ecological validity of the findings. The 30-minute design task, while practical for an experimental setting, cannot fully replicate the complexity, depth, and iterative nature of real-world design projects that typically unfold over days, weeks, or even months. In professional contexts, designers engage with tools repeatedly, developing familiarity and establishing personalized workflows that could significantly alter how prompting assistance is utilized and valued.

The effectiveness of prompting assistance might vary considerably in sustained professional contexts where initial novelty has worn off and deeper integration challenges become apparent. The platform-specific nature of the implementation introduces another limitation. PromptlyUX was developed specifically as a Figma plugin, which constrains the insights to this particular design environment and user base. Different design tools such as Adobe XD, Sketch, or Framer might present unique integration challenges, interface constraints, or user expectations not captured in this study. The transferability of findings across platforms cannot be assumed without further investigation, particularly as each design environment has its own interaction paradigms and technical architectures. A potential novelty effect must also be considered when interpreting the positive responses. Participants' enthusiasm and satisfaction might be partially influenced by the novelty of AI assistance rather than its sustained utility in everyday design work. The excitement of experiencing new technology often produces temporarily heightened positive reactions that may diminish with prolonged use. Longitudinal studies would be necessary to evaluate the persistence of benefits over time and to determine whether the observed advantages maintain their significance once the initial novelty has dissipated.

Furthermore, the specific design challenge, creating a diabetes monitoring dashboard for children, represents only one type of UX/UI design task with particular characteristics and constraints. Different domains (such as e-commerce, entertainment, or enterprise software) and various types of design challenges (from information architecture to micro-interaction design) might benefit differently from prompt assistance. The generalizability of findings across diverse design contexts remains uncertain without additional validation across a broader spectrum of design scenarios.

Finally, technical limitations related to the underlying AI model must be acknowledged. The study relied specifically on GPT-4's capabilities, which represents a particular moment in the rapidly evolving landscape of large language models. The findings may not generalize to other LLMs with different performance characteristics, training approaches, or to future generations of AI technologies that may resolve current limitations or introduce new capabilities and challenges. The effectiveness of prompting assistance is inherently linked to the capabilities and limitations of the underlying model, making these findings somewhat time-bound in the context of rapid technological advancement. These limitations, while important to acknowledge, also present valuable opportunities for future research to build upon and refine our understanding of AI-assisted prompting in design contexts. Each constraint points toward specific directions for extending this work and testing its boundaries across different populations, time scales, platforms, and technological conditions.

7.3 Significance

This research makes several significant contributions to the field of AI-integrated UX/UI design: First, it provides empirical evidence that structured prompting support can bridge the gap between AI capabilities and designer needs, addressing a critical barrier to adoption identified in previous literature. The statistically significant differences in satisfaction and adoption intent demonstrate that prompt assistance isn't merely a convenience but a transformative factor in AI integration. Second, the development of PromptlyUX offers a practical model for embedding prompt engineering principles directly into design tools. By operationalizing theoretical concepts from prompt engineering research into tangible features like dynamic suggestion tabs, contextual follow-ups, and domain-specific templates, the study translates abstract principles into functional design patterns that can inform future tool development. Third, the research extends our understanding of cognitive load in AI-assisted workflows. The reduction in mental demand and frustration reported by Group A participants confirms that well-designed prompting systems can serve as effective cognitive scaffolding, allowing designers to focus on creative decision-making rather than query formulation. Finally, the study contributes to the evolving discourse on AI's role in creative professions. By positioning AI as a co-pilot rather than an autonomous agent, PromptlyUX demonstrates how prompting assistance can enhance designer agency rather than diminish it, a crucial consideration as AI becomes increasingly embedded in creative workflows.

7.4 Future Research Directions

This research opens several promising avenues for future investigation that could extend our understanding of AI-assisted prompting in design contexts and further enhance the integration of AI tools into creative workflows. Longitudinal implementation studies represent a particularly important direction for future work. While the current study provides valuable insights into immediate user responses and short-term performance, extended research examining how prompt assistance impacts design outcomes and workflows over weeks or months would provide deeper insights into the sustained benefits and potential challenges of AI integration. Such studies could track changes in prompting behavior, adaptation strategies, and evolving perceptions of AI assistance as designers move beyond initial impressions to incorporate these tools into their established practices. This longitudinal perspective would help address questions about the persistence of benefits beyond novelty effects and reveal how designer-AI relationships mature over time.

Future research should also explore expanded prompting paradigms that move beyond text-based interactions. Multimodal prompting approaches that combine text, visuals, and interactive elements could potentially bridge the gap between designers' visual thinking processes and the predominantly language-based interfaces of current AI systems. Similarly, collaborative prompting models where multiple designers contribute to prompt formulation could reveal new dynamics in team-based design contexts where diverse perspectives and requirements must be synthesized into coherent AI instructions. These alternative paradigms might address limitations in current prompting approaches while opening new possibilities for creative expression and collaborative design.

The development and evaluation of domain-specific prompt libraries represents another valuable research direction. Different design specializations such as service design, product design, information architecture, or interaction design may benefit from specialized prompt collections that reflect their unique terminologies, methodologies, and evaluation criteria. Research exploring how prompting needs vary across disciplines could lead to more tailored AI assistance tools that better align with the specific challenges and objectives of different design fields. Such specialization could potentially increase the relevance and utility of AI tools across the diverse landscape of design practice. Cross-tool integration studies could address the reality that most designers work across multiple platforms throughout their design process. Research exploring how prompting assistance might function seamlessly across different design environments could address workflow fragmentation and support more cohesive AI integration throughout the design lifecycle. This might involve investigating cloud-based prompting systems that maintain context across applications, standardized prompting protocols that work consistently across platforms, or integration approaches that respect the unique strengths of different design tools while providing consistent AI assistance.

As AI systems grow more sophisticated, research into adaptive prompting systems that learn from designer interactions represents an exciting frontier. Studies examining how AI assistants might analyze interaction patterns to personalize prompting assistance over time could enhance relevance and reduce repetition. Such systems might adapt to individual working styles, learn domain-specific vocabularies, and progressively refine their understanding of a designer's preferences and priorities. This personalization could potentially overcome some of the limitations of generic prompting approaches while creating more intuitive, responsive design assistants. The ethical dimensions of AI-assisted prompting deserve dedicated investigation as these tools become more prevalent in design practice. Future work should address emerging questions such as how prompt assistance might impact design originality and diversity, the potential for embedded biases in prompt suggestions, appropriate attribution when AI contributes significantly to design outcomes, and concerns around intellectual property and creative control. Research in this area is essential to ensure that AI tools enhance rather than undermine the values and ethical principles that guide responsible design practice.

Finally, accessibility and inclusivity in AI prompting systems represent critical areas for future investigation. Research into how prompting assistance might be designed to support designers with different abilities, working styles, technical expertise, and cultural backgrounds would ensure these tools promote equity in AI-assisted design. Studies might explore multimodal interaction options, cultural adaptability in prompt libraries, or flexibility in interaction paradigms to accommodate diverse user needs. This work would help ensure that the benefits of AI assistance are available to all designers, regardless of individual differences or constraints. These future research directions, taken together suggest a rich and diverse line of future research that could substantially advance our understanding of human-AI collaboration in design contexts. By building on the foundation established in this study, future work can continue to refine and extend prompting assistance approaches, ultimately creating more intuitive, powerful, and accessible tools that enhance human creativity rather than replacing it.

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Appendices

A. PromptlyUX

Feature 1: Onboarding Survey questions

```
// Project Description
const projectDescription = {
    question: 'Give a short description of your current design project.',
    placeholder: 'Briefly describe your project goals and context...'
};

// Target Audience
const targetAudience = {
    question: 'What is the target audience for your design?',
    placeholder: 'Describe your target audience, their needs, and characteristics...'
};

// Project Type
const projectType = {
    question: 'What type of project are you working on?',
    options: [
        'Website',
        'Mobile App',
        'Desktop Software',
        'Other'
    ]
};

// Project Goals
const projectGoals = {
    question: 'What is the main goal of your design project?',
    options: [
        'Usability',
        'Accessibility',
        'Aesthetics',
        'User Engagement',
        'Efficiency',
        'Learnability'
    ],
    multiple: true
};

// Figma Skill Level
const figmaSkillLevel = {
    question: 'What's your level in Figma?',
    options: [
        'Beginner',
        'Intermediate',
        'Advanced',
        'Expert'
    ]
};

// Preferred Design Style
const preferredDesignStyle = {
    question: 'Do you have a preferred design style?',
    options: [
        'Modern',
        'Experimental',
        'Professional',
        'Playful',
        'Informative',
        'No preference'
    ]
};

// Product Complexity
const productComplexity = {
    question: 'How complex is your final product?',
    options: [
        'It has 1-3 purposes',
        'It has 3-5 purposes',
```

```
        'It has 5+ purposes',
        'I am unsure'
    ]
};
// Project Purposes
const projectPurposes = {
    question: 'Describe some of the purposes.',
    placeholder: 'E.g. conversion (webshop), informative (news/blog), community (social
network), entertainment (streaming), etc.'
};

// Design Process Stage
const designProcessStage = {
    question: 'What stage are you in within the design process?',
    options: [
        'Research',
        'Wireframing',
        'Prototyping',
        'User Testing'
    ]
};

// Additional Guidelines
const additionalGuidelines = {
    question: 'Do you have other guidelines or remarks regarding this project?',
    placeholder: 'Add any additional guidelines, requirements, or remarks that might be
relevant...'
};
```

Feature 2: Follow-Up Prompt

```
const systemPrompt = `You are a specialized AI assistant focused on generating engaging
follow-up questions for UI/UX design conversations. Your role is to analyze the conversation
history and identify key discussion points and generate follow-up question prompts.

Guidelines for follow-up question prompts:
    - Keep question prompts concise (under 100 characters)
    - Focus on the most recent assistant response
    - Prefer "how" and "what" questions over yes/no questions
    - Include specific references to mentioned design elements or concepts

Example good question prompts:
    - "Could you elaborate on [part of previous response]?"
    - "How would this design pattern impact user engagement?"
    - "What metrics would measure this solution's effectiveness?"
    - "Which accessibility considerations apply to this component?"`;

const userPrompt = 'Generate a focused follow-up question about the most recent topic
discussed in our conversation.'
```

Feature 3: Dynamic Prompt Suggestion Tabs

```
const systemPrompt = `You are a prompt questions suggestions generator to ask an AI
chat.Generate a detailed prompt which I can send to a large language model based on the given
title. [...]

IMPORTANT GUIDELINES:
    Focus on the PROJECT CONTEXT.
    Generate DIVERSE suggestions that cover DIFFERENT aspects of the project.
    AVOID suggesting topics similar to the recent conversation topics: ${recentTopics.join(',
')}.
    Ensure the prompts avoid using terms such as 'create,' 'build,' 'design,' 'develop,' or
any language that implies direct design actions.
    Make the prompts detailed yet concise.
    Keep titles very short (1-2 words).
    DIRECTLY REFERENCE specific project details in your prompts, such as:
        "With this project description ${projectData.projectDescription || 'No project
description provided'}, ..."
        "Considering that this project is for ${projectData.targetAudience || 'the target
audience'}, could you..."
        "Given that the project is in the ${projectData.designStage || 'current'} stage, how
might..."
        "With the goal of ${projectData.mainGoals.length ? projectData.mainGoals[0] :
```

```
'improving user experience'}, what..."
        "For a ${projectData.projectType || 'design'} project with ${projectData.complexity ||
'this complexity'}, how..." [...]`;


const userPrompt = `Generate two DIVERSE prompt suggestions based on the project context:
${JSON.stringify(projectContext)} and on the recent conversation
${JSON.stringify(conversationContext)}.

Remember to:
    Suggest topics DIFFERENT from the recent topics
    Cover varied aspects of the project
    DIRECTLY REFERENCE specific project details in your prompts (target audience, project
type, design stage, goals, etc.)
    Frame questions in a way that acknowledges the specific project context, like "Given that
you're designing for ${projectData.targetAudience || 'your audience'}..." or "Considering this
is a ${projectData.projectType || 'design'} project..."`;
```

Feature 4: Prompt Library

```
const presetPrompts = {
    'UX Research': {
        'User persona': `Create a detailed user persona for [product/service] that includes
demographic information, behaviors, goals, frustrations, and motivations. Include a
day-in-the-life narrative that shows how they interact with products like mine, their
decision-making process, and key touchpoints where my solution could add value.`,

        'User journey map': `Help me develop a comprehensive user journey map for [specific
user persona] interacting with [product/service/process]. Include all stages from awareness to
advocacy, detailing their actions, thoughts, emotions, pain points, and opportunities for
improvement at each touchpoint. Highlight critical moments that could make or break their
experience.`,

        'Target audience': `Define a precise target audience for [product/service/content],
including primary and secondary segments. For each segment, outline demographic
characteristics, behavioral patterns, media consumption habits, purchasing power, and the
specific problems my [product/service] would solve for them. Explain why this audience is
strategically valuable.`,

        'Behavior analysis': `Analyze the typical behavioral patterns of [specific user group]
when they [relevant activity]. Include their decision triggers, habitual actions,
environmental influences, psychological factors, and how these behaviors have evolved over
time. Focus on identifying unexpected or counterintuitive behaviors that might inform product
design.`
    }
};
```

Feature 5: Generate Prompts

```
const systemPrompt = 'You are a helpful assistant that generates prompts for ChatGPT. Generate
each prompt as a separate paragraph WITHOUT numbering them, OR giving them titles (e.g.
"Prompt 1", "Prompt 2", "Prompt 3"), OR adding quotation marks: JUST provide the prompt text.'

Make the prompts help with the ux design process (for example: "What is the industry standard
for [topic]?" "Help me create interview questions for [target users] to understand their needs
around [topic]." "Summarize user pain points from this set of notes: [paste notes]." "What
personas can I create based on the following data: [user quotes or data]?" "What are effective
color schemes for a mental health app and why?")

Do not use lot of actionable verbs as ChatGPT is unable to design, develop, edit, etc.

Make the prompts SHORT and GENERAL, not specific to a product or service. Refer to
topics/users/data in [brackets] instead.

${overviewText ? `Include the following project information in your
considerations:\n${overviewText}` : ''}

const userPrompt = `Generate THREE different prompts for ChatGPT based on the following topic:
"${userTopic}".`
```

B. Design Brief

DESIGN ASSIGNMENT

INTRODUCTION

Objective: Design a health dashboard application through Figma.
Prototype or wireframe at least 1 page, you can make it as elaborate as you want. Other plugins are permitted, but use the *PromptlyUI* plugin as much as possible to assist with your design workflow.

Target group: Children with Type 1 Diabetes and their caregivers
These are children (ages 6-14) managing a complex chronic condition that requires continuous monitoring and adjustment throughout their daily lives. If needed, use the AI tool to generate insights about this group.

Imagine this platform serves as a digital health hub where these children and their caregivers can:

- Monitor blood glucose levels, insulin dosing, and carbohydrate intake in age-appropriate ways
- Track physical activity and its effects on blood sugar levels
- Connect with healthcare providers and school nurses to share critical health data

USER PERSONA

Create a detailed user persona representing a user of this platform.

- Include for example name, age, background, goals, frustrations, and behavior patterns.
- Consider how this person interacts with the technology.

Deliverable:
One (or more) user persona(s) that fit the target group.

STYLE GUIDE

Generate a style guide based on key needs such as:

- Child-friendly and approachable design that doesn't feel intimidating
- Color coding systems for vital levels

Deliverable:
One frame in Figma with a comprehensive style guide including color palette, typography, iconography, and visualization examples that support both children's engagement and medical accuracy.

DESIGN

Prototype (or wireframe) one page of the dashboard application

- Think about core functionalities and make a list of requirements.
- Make the design age appropriate, simple, and functional.
- Create an application for mobile users.

Deliverable:
Prototype (or wireframe) of one page of a health application for sick children

Once you complete the three deliverables, please let me know.
There will be some questions about the tool afterwards.

C. Survey Questions

Pre-Test Demographics

1. What is your age?
2. What is your gender?
3. What is your country of origin?
4. How many years of experience do you have in UI/UX design?
5. What title do you identify with most?
6. Have you used AI-powered tools in your design workflow before? *(Yes/No)*
7. If yes, which AI tools have you used in your design workflow?
8. How frequently do you use AI tools in your workflow?
   from 1 (Never) to 5 (Daily)
9. How would you describe your current attitude towards AI tools in design?
   from 1 (Very skeptical) to 5 (Very positive)
10. On a scale of 1-5, how confident do you feel in your ability to write effective prompts for AI tools?
    from 1 (Not confident at all) to 5 (Very confident)

Post-Task Evaluation

1. How did you feel about the time it took to complete this task?
   from 1 (Much slower than usual) to 5 (Much faster than usual)
2. Would you say the AI tool helped you complete the task more efficiently than your usual workflow?
   from 1 (No, it made the task much harder) to 5 (Yes, significantly)
3. System Usability Scale (SUS)
   from 1 (Strongly Disagree) to 5 (Strongly Agree)
   a. *I think that I would like to use this AI system frequently*
   b. *I found the AI system unnecessarily complex*
   c. *I thought the AI system was easy to use*
   d. *I think that I would need the support of a technical person to use this AI system*
   e. *I found the various functions in this AI system were well integrated*
   f. *I thought there was too much inconsistency in this AI system*
   g. *I would imagine that most people would learn to use this AI system very quickly*
   h. *I found the AI system very cumbersome to use*
4. Cognitive Load (NASA-TLX workload index)
   from 0 (Very Low) to 100 (Very High)
   a. *Mental Demand: How mentally demanding was the task?*
   b. *Physical Demand: How physically demanding was the task?*
   c. *Temporal Demand: How hurried or rushed was the pace of the task?*
   d. *Performance: How successful were you in accomplishing what you were asked to do?*
   e. *Effort: How hard did you have to work to accomplish your level of performance?*
   f. *Frustration: How insecure, discouraged, irritated, stressed, and annoyed were you?*

5. Only for Group A: Did the prompting assistance improve your ability to integrate AI into your workflow? Likert scale *from 1 (Very Dissatisfied) to 5 (Very Satisfied)*
6. How satisfied are you with the integration of AI tools in this design task? Likert scale *from 1 (Very Dissatisfied) to 5 (Very Satisfied)*
7. Would You Use AI in Your Workflow Again? *(Yes/No/Maybe)*

Interview questions

1. What was the most helpful aspect of the AI system?
2. What was the most challenging aspect of using the AI system?
3. For Group A only: How did prompting assistance affect your design process?