

CANVIL: Designerly Adaptation for LLM-Powered User Experiences

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Advancements in large language models (LLMs) are poised to spark a proliferation of LLM-powered user experiences. In product teams, designers are often tasked with crafting user experiences that align with user needs. To involve designers and leverage their user-centered perspectives to create effective and responsible LLM-powered products, we introduce the practice of *designerly adaptation* for engaging with LLMs as an adaptable design material. We first identify key characteristics of designerly adaptation through a formative study with designers experienced in designing for LLM-powered products ($N = 12$). These characteristics are to 1) have a low technical barrier to entry, 2) leverage designers' unique perspectives bridging users and technology, and 3) encourage model tinkering. Based on this characterization, we build CANVIL¹, a Figma widget that operationalizes designerly adaptation. CANVIL supports structured authoring of system prompts to adapt LLM behavior, testing of adapted models on diverse user inputs, and integration of model outputs into interface designs. We use CANVIL as a technology probe in a group-based design study (6 groups, $N = 17$) to investigate the implications of integrating designerly adaptation into design workflows. We find that designers are able to iteratively tinker with different adaptation approaches and reason about interface affordances to enhance end-user interaction with LLMs. Furthermore, designers identified promising collaborative workflows for designerly adaptation. Our work opens new avenues for collaborative processes and tools that foreground designers' user-centered expertise in the crafting and deployment of LLM-powered user experiences.

CCS Concepts: • **Human-centered computing** → **Interaction design process and methods**; **Empirical studies in collaborative and social computing**.

Additional Key Words and Phrases: large language models, user experience, design practice

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1 INTRODUCTION

A paradigm shift is underway for integrating artificial intelligence (AI) capabilities into everyday user-facing technologies. Large pre-trained AI models, most notably large language models (LLMs), have versatile natural language capabilities that unlock novel interactive techniques and interfaces

*Work done while at Microsoft Research.

¹CANVIL is available for public use at <https://www.figma.com/community/widget/1277396720888327660>.

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for more intuitive and customizable user experiences across a wide spectrum of applications [2, 71, 93, 104]. However, these promises also come with numerous concerns. Integrating LLMs into a domain without careful consideration of the user contexts surrounding model use and implementation of behavioral guardrails for the model may result in user experiences that perpetuate societal biases [83], threaten users’ sense of well-being [81, 86], or otherwise do harm [22, 84].

As technology development practitioners, designers² are uniquely positioned to mitigate these concerns [30, 50, 91, 105, 107]. Designers’ work often involves aligning technological capabilities with user needs, such that the technology addresses (or makes progress towards addressing) pain points identified in user research [30, 90]. Designers are trained in human-centered design methods that allow them to understand users and usage contexts, prototype potential solutions with relevant technology, and iterate on those solutions based on their understanding of users or user feedback [6]. Yet, prior work has shown that designers face diverse challenges working with AI [92, 106]. These challenges include procedural ones, such as difficulties collaborating with the engineering teams training the models [90, 92], as well as instrumental ones, such as lacking means to effectively work with the models [30, 91, 105]. In efforts to address this, researchers have situated AI as a design material to highlight exploring material considerations—e.g., the technology’s capabilities, limitations, and adaptability [49]—for designers to better understand and apply AI in the context of their design problems [24, 28, 105]. A good “designerly understanding” of AI can help designers ideate on new AI-powered design ideas, mitigate AI’s varying impact for different user scenarios, collaborate with design and non-design practitioners, and reinforce user-centered perspectives amongst the team and throughout the product development cycle [50, 95].

The advent of LLMs introduces new opportunities for engaging with AI as a design material. First, adaptability emerges as a key materialistic property of LLMs. LLMs are responsive to adaptation via fine-tuning [5, 23, 37, 70] and prompt-based methods [65, 66, 103]. In fact, due to resource-intensive training of LLMs, it has become a standard practice for individual developers and development teams to adapt “base” LLMs from a small handful of providers (e.g., Anthropic, Google, OpenAI) [71] for improved performance in domain-specific tasks. Moreover, natural language interaction and adaptation democratizes AI experimentation for practitioners—including designers—traditionally excluded from AI conversations due to limitations in technical expertise [50, 73]. Despite this, there has been limited exploration of designers’ interaction with—let alone adaptation of—LLMs in practice, with untapped opportunities for designers to contribute to LLM-powered product development.

In this paper, we introduce the practice of *designerly adaptation of LLMs* (henceforth “designerly adaptation”) to showcase new opportunities for designers to harness LLMs as an adaptable design material. We first characterize this new practice through a formative interview study with 12 designers experienced in designing for LLM-powered products and features. Our study reveals that desirable characteristics of designerly adaptation include execution via natural language prompt-based methods, leveraging designers’ user-centered perspectives and expertise, and encouraging iterative tinkering with models.

While these desiderata align with those surfaced in prior work [30, 90, 106], the practical significance of satisfying them in design workflows remains unclear. To investigate, we build CANVIL, a technology probe in the form of a Figma³ widget that operationalizes designerly adaptation. CANVIL enables designers to adapt LLMs within their Figma canvases via system prompting [57, 66] and integrate outputs from adapted models into their designs. We use CANVIL in a task-based design study with 6 groups of 17 designers total to understand whether and how designerly adaptation can assist

²We consider designers to be anyone who has an active, hands-on role in designing the user experience of a product and/or feature. This includes job titles such as UI and UX designer/researcher, content designer, and product designer.

³Figma is a popular collaborative design tool: <https://www.figma.com/>.

in crafting LLM-powered user experiences. We find that through designerly adaptation, designers steered LLM behavior with user needs, derived interface affordances to enhance user interaction with LLMs, and recognized promises in collaborative adaptation to share resources and knowledge with design and non-design stakeholders. They were optimistic about integrating designerly adaptation into their own workflows and noted procedural and ethical questions to address in practice.

Equipped with findings from both studies, we propose a concrete workflow for designerly adaptation to offer a tangible launchpad for researchers and practitioners to further explore, critique, and iterate on this practice. We end by underscoring the potential of tools for collaborative AI tinkering, while reflecting on materiality’s impact on social practices within product teams.

Concretely, our work makes the following contributions:

- Insights from a formative study with designers experienced in crafting LLM-powered user experiences, from which we assemble a characterization of designerly adaptation—a new practice by which designers engage with LLMs as an adaptable design material.
- CANVIL, a technology probe in the form of a Figma widget that operationalizes designerly adaptation.
- Insights from an empirical exploration of how designers engage in designerly adaptation in a task-based design study.
- A discussion of our work’s implications on (collaborative) design and beyond, including a proposed workflow for designerly adaptation to orient future work.

2 RELATED WORK

To situate our work, we review prior literature in AI as a design material, approaches to LLM adaptation, and tools for interactively working with AI models.

2.1 AI as a Design Material

Robles and Wiberg argue that recent advances in computational technologies bring about a “material turn”—a transformation within interaction design that allows for the shared use of material metaphors (e.g., flexibility) across physical and digital worlds [80]. Indeed, prior works have discussed AI as a *design material* [8, 24, 29, 30, 50, 55, 105–107], and highlighted why AI’s materiality can make it uniquely difficult to design with [8, 24, 50, 92, 106]. AI is often treated as a black box to non-technical stakeholders such as designers, making it challenging to tune user interactions to often unpredictable and complex model behavior [8, 105]. In addition, AI’s technical abstractions are often divorced from concepts designers are familiar with [92], and designers consequently struggle with creatively using or manipulating the material to generate design solutions [30, 50]. AI models are also non-deterministic and fluid in nature—they may evolve with new data or user input, and can be intentionally steered towards desirable behaviors with choices of data, algorithm, parameter, and so on [106]. Without a concrete material understanding to begin with, designers are unable to grasp the nature of these uncertainties [91, 105] or the opportunities to shape the design materials for desirable UX [50]. Yang et al. [106] showed that these challenges of working with AI as a design material persist through the entire double-diamond design process—from identifying the right user problem to be solved by AI to designing the right UX to solve the user problem.

Researchers and practitioners have developed processes and tools to alleviate some of these challenges. ProtoAI [91] combines exploration of models with UI prototyping, while advocating for designers’ active shaping of the AI design material (e.g., choosing models and setting parameters) by user needs. Feng et al. [30] found that hands-on “fabrication” of the design material through a UI-based model training tool bolstered understanding and connection between AI properties and UX goals. fAllurenotes [62] is a failure analysis tool for computer vision models to support

designers in understanding AI limitations across user groups and scenarios. Other efforts include process models [92] and “leaky abstractions” [90] that facilitate collaboration between designers and model developers, and human-AI design guidelines [3, 33, 59].

Recent advances in LLMs simultaneously alleviate and exacerbate some of the aforementioned challenges. The barrier to tinkering with AI has significantly lowered thanks to the use of natural language as a primary mode of interaction and easily accessible tools such as ChatGPT. Concerns, however, have also arisen over the lack of explainability and transparency in LLMs due to their complex technical architectures [51]. Yet, because of LLMs’ powerful capabilities, there is significant interest in exploring their integration into user-facing technologies [71, 74, 88]; as such, designers should be prepared to work with them as a design material [45]. Despite this, we have yet to understand designers’ current approaches and desiderata when crafting LLM-powered user experiences. Our work contributes both empirical knowledge and tooling via a technology probe to this space.

2.2 Adaptation of Large Language Models

A fundamental property of LLMs not present in their smaller predecessors is the ease with which their behavior can be adapted [13, 65]. While the breadth of LLMs’ out-of-the-box capabilities may seem impressive, researchers have recognized the importance of adapting LLMs for enhanced performance under specific domains and tasks [23, 37, 95, 103, 104], and aligning model behavior with human preferences and values [5, 27, 70]. Adaptation has thus been a topic of interest to both the AI and HCI communities [47].

Adaptation may take on many forms. A pre-trained model may undergo *fine-tuning*, a process by which additional layer(s) of the neural network are trained on a task-specific dataset [23]. Popular approaches to fine-tuning include instruction tuning [70, 98], reinforcement learning with human feedback (RLHF) [19, 70], and direct preference optimization (DPO) [76]. More computationally efficient variants, such as low-rank adaptation (LoRA) [37], have also garnered attention.

Adaptation can also occur without modifying the model itself, through system prompting.⁴ Different from one-off prompting, system prompting applies to all individual user inputs for how the model should behave (e.g., “*always respond in a concise manner*”), often targeting an application domain. OpenAI’s API provides a “System” field to specify system prompts [64, 66], which have been shown to be effective at modifying model behaviors [21, 65, 82]. For instance, a line of work explored instructing the model to behave with a certain “persona” to elicit desirable or adversarial model behaviors [18, 21, 82, 97, 100]. However, system prompts can be challenging to author [109], and there is not yet an established “gold standard” for prompt writing, system or otherwise. Researchers and practitioners have attempted to derive useful prompting formats based on empirical exploration; these include in-context learning (i.e., by providing desired input-output examples) [13, 102, 110], chain-of-thought reasoning [99], and instruction-following [43, 69]. Industry recommendations have also emerged for system prompts, encouraging the specification of elements such as context specification (e.g., “*You are Yoda from Star Wars*”), task definition (e.g., “*You respond to every user input as Yoda and assume the user is a Padawan*”), and safety guardrails (e.g., “*If the user requests inappropriate or offensive responses, you must respectfully decline with a wise Yoda saying*”) [57].

In our work, we examine and support *designerly adaptation* of LLMs—whether and how designers can contribute to model adaptation for user-facing products through system prompting. We develop a characterization of the term through our formative study, and then build a technology probe to operationalize it in design practice. In building our probe, we draw from recommended best

⁴System prompting has also been referred to as “system messaging” and “metaprompting” [57]. We use “system prompting” in our paper to align with terminology in prior academic work [97].

practices for system prompting, but acknowledge that these practices may shift over time and that our work reflects just one possible instantiation of these practices.

2.3 Interactive Tools for Steering AI Behavior

Literature at the intersection of HCI and AI has introduced a wide range of interactive techniques and tools to aid humans in training and adapting AI models, ranging from ones supporting data scientists to perform data wrangling [34, 44, 53, 96, 101], model training and evaluation [1, 7, 14, 32, 40, 58, 78], managing model iterations [36, 79], and so on, to those allowing for “human-in-the-loop” paradigms at various stages of the model development pipeline, including data annotation [16, 61, 77, 85, 87], output correction [10, 11], integration testing [17], and explainability [46, 63, 75].

There has also been a long-standing interest in “democratizing AI” for domain experts or practitioners without formal technical training to steer model behaviors. Interactive machine learning (iML) [26] is a field responding to this interest by advocating for interactive and incremental model steering through intuitive interfaces and tightly coupled input-evaluation feedback loops. For instance, interfaces for transfer learning [60] have enabled non-expert users to transfer learned representations from a larger model to a domain-specific task. Tools have also encouraged non-expert exploratory tinkering of AI models through visual drag-and-drop UIs [15, 25, 52, 54]. Teachable Machine [15] is one such tool that allows users to train models for image, video, and audio classification. Rapsai [25] is a visual programming pipeline for rapidly prototyping AI-powered multimedia experiences such as video editors. In an era where formal knowledge about AI is limited to a small handful of technical experts, these tools also serve to demystify AI for everyday users.

With the onset of language models, barriers to experimenting with AI have lowered even further, paving the path for a new generation of interactive AI tools. Sandbox environments such as OpenAI’s playground [67] require no prerequisites besides a grasp of natural language to prompt the model and steer model behavior. However, relying on unstructured natural language alone can be daunting and ineffective. Many tools have risen to the challenge to support prompt engineering with more structured tinkering. Prompt chaining is one such approach [4, 93, 103, 104], by which users can use a node-based visual editor to write prompts for simple subtasks and assemble them to solve a larger, more complex task. PromptMaker [41] and MakerSuite [38] allow the user to rapidly explore variable-infused prompts and few-shot prompting, while ScatterShot [102] helps specifically with curating few-shot prompting examples.

Despite advancements in tooling, support for designers to work with LLMs as an adaptable design material remains limited. Domain-agnostic tools for tinkering with models may not be well-integrated into design workflows, a primary consideration for designers when deciding whether to adopt those tools [29]. Tools that offer integration with design environments (e.g., PromptInfuser [72, 73]) support prototyping with LLMs, but not necessarily deeper adaptation of model behavior. Our work situates interactive adaptation within familiar design environments and processes.

3 FORMATIVE STUDY

Working with AI, especially LLMs, is an emerging practice in the field of UX [28, 92, 106, 108]. We wanted to understand designers’ experiences working on LLM-powered products and features amidst industry-wide shifts towards LLMs [71] as an initial step in our research. We hence conducted a formative study where we interviewed designers about their awareness of, involvement in, and desiderata around designing LLM-powered user experiences.

3.1 Method and Participants

We conducted 30-minute 1:1 virtual interviews with 12 designers at a large international technology company, where LLM-powered features and products are actively explored. All interviews

were conducted in June and July 2023. At the time of the study, all participants were working on products or services that leveraged LLMs in some capacity; LLM application areas spanned conversational search, domain-specific data question-answering (QA), recommendation, text editing and generation, and creativity support tools. Participant details can be found in Table 1 of Appendix A.

Our interviews were semi-structured and revolved around the following topics:

- **Awareness:** to what extent are designers aware of LLMs’ capabilities, limitations, and specifications in the context of their product(s)?
- **Involvement:** to what extent are designers involved in discussions or activities that shape where and how an LLM is used in their product(s)?
- **Desiderata:** what do designers desire when crafting LLM-powered user experiences, with regards to both processes and tools?

Each participant received a \$25 USD gift card for their participation. All interviews were recorded and transcribed. Our study was reviewed and approved by the company’s internal IRB.

The first author performed an inductive qualitative analysis of the interview data. This process started with an open coding round in which initial codes were generated, followed by two subsequent rounds of axial coding in which codes were synthesized and merged into higher-level themes. The codes and themes were discussed with research team members at weekly meetings. Other research team members also offered supporting and contrasting perspectives on the codes by writing their own analytic memos, which were also discussed as a team.

3.2 Findings

We present summaries of our major themes as findings below. While our research did not focus specifically on model adaptation to start, we saw adaptation emerge as a connecting thread across many of our participants’ experiences; as such, we present our findings through the lens of adaptation. Additionally, we use our findings to motivate and define *designerly adaptation*, culminating in a concrete characterization of the term in Section 3.3.

3.2.1 Adaptation was seen as a central materialistic property of LLMs. Designers recognized that products delivering compelling, robust user experiences were not powered by out-of-the-box “base” LLMs, but required adaptation and, in some cases, grounding in other sources. P5 gave an example where an out-of-the-box model inappropriately prompted the user for a riddle in a workplace setting: “[The experience] is not quite right, cause it’s in [workplace software] and it’s like, tell me a riddle. I’m at work!” Those working in the domain of conversational search knew the model had to be connected to a search engine to ensure information relevance and reliability, so that they are “not just giving [the user] the chatbot” [P9].

The ability to steer an LLM with natural language enabled designers to envision more flexible and adaptable AI-powered user experiences than working with traditional AI models. Some were familiar with how lightweight adaptation techniques, such as writing system prompts, can be used to specify model behaviors based on desirable UX. P12 discussed an example of how this may work in an entertainment system setting:

“You might want to generate enthusiasm more, right? So the LLM that goes over there might have a UX layer that feels different. It should. I hope it does. The system prompt can say, remember, you’re a machine that wants to get users enthused.” [P12]

Participants recognized that the adaptability of LLMs allows their team to more easily create multiple versions of LLM-powered features in one product. P2 shared that they were already seeing multiple versions of the same model customizing experiences within their product: “There are actually 3 incarnations of the same model, each with slightly different parameters [...] based on the

prompt that users give, we select which of those 3 incarnations we wanna use.” Participants also believed adapting the model’s ability or behaviors for different user groups or contexts can help create more equitable experiences. For example, P4 and P7 both stated a design goal for their products (in conversational search and domain-specific question-answering, respectively) is to accommodate non-technical users, which can be achieved if the model can *“tailor the language depending on technical ability, and gradually introduce [users] to more complicated concepts and terminology.”* [P7]. Adaptation thus not only allows user experiences to more flexibly accommodate existing user groups, but also to expand to serving new ones.

3.2.2 Designers were often not involved with adaptation, but desired more involvement. Even though designers found adaptation inextricably linked to UX considerations, they were typically not involved in adaptation. Some were unsure of how or by whom adaptation is performed and suspected that it was engineers: *“I would say [adaptation]’s probably something that was decided by the engineering team [...] prompt engineering is more so on the [technical] side of things.”* [P2]. Many knew for a fact that it was engineers and data scientists who adapted the models and relied on them for information about model behavior. This often got cumbersome quickly. P11 explained that in their product, designers set character limits for LLM-generated summaries in the UI, but were unable to directly specify and experiment with the model’s output length. Instead, P11 relied on engineers to adapt on their behalf: *“I was asking what the difference in summary looks like with 50, 100, and 150 characters. Then [the engineers] would go back and test it and then they would just share the results, like here’s what 50 characters looks like. Here’s what 100 looks like.”* P12 experienced a similar procedure and stated that the feedback loop can take as long as a couple weeks. Ideally, they wanted the experimentation to happen *“in real time.”*

The combination of 1) adaptation and UX being closely intertwined, and 2) designers’ exclusion from the adaptation process, led to a sentiment echoed by the far majority of our participants: designers should have an active role in model adaptation. Indeed, designers are *uniquely positioned* to contribute to adaptation through their user-centered lens. For example, P4 shared that they naturally gravitate to persona-based reasoning in their design process: *“How would I use this? How would my mom use this? Taking on [the perspective of] different personas made sense to me.”* This type of reasoning is critical for adapting user experiences to accommodate diverse user needs and usage contexts. Indeed, P10 caught their model’s inability to properly recognize some acronyms users of their product might come across and devised a solution with their team: *“I found that [the model] doesn’t know what to do with the acronyms so we floated the idea of having glossary of industry jargon and acronyms [in the system prompt].”*

Because of this, many participants were advocates for designers performing adaptation, and considered UX goals as indispensable in this process. P4 shares: *“Who better to involve in this process than people whose job it is to think deeply about [the UX]? At the very least, system prompts shouldn’t be written without an understanding of what the end UX goals are.”* P9 agreed, saying that designers can offer strategic contributions with user-centered thinking: *“It’s super important for designers to think through ideas and make it intuitive for users and help come up with compelling [user] scenarios [...] I think design has a bigger opportunity to have a seat at the table strategy-wise.”* On a higher level, P12 pointed out that model adaptation can be a contemporary extension of efforts around crafting product voice and tone, which designers are already familiar with: *“UX designers and content designers are very attuned to and have pretty much owned the story around voice and tone of products, and have for years and years.”*

We see a broad consensus among participants that there is both demand and opportunity for designers to engage in adaptation. We therefore propose that designerly adaptation should leverage designers’ existing expertise and workflows to enhance model behavior in user-centered ways.

3.2.3 Designers lack support to tinker with and adapt LLMs. Overall, participants felt limited by current tools and resources to tinker with LLMs. These findings echo prior work that finds that the inability to directly access the models and experiment with their capabilities and limitations (i.e., “tinkering”) is a primary challenge in the design process for AI-powered user experiences [90, 106]. Many participants emphasized the importance of “tinkering” to understand model capabilities and limitations to inform design ideation and interface prototyping. After some hands-on experience with the model, P2 said they could much more clearly “*see or gauge the power of the language model,*” while P9 tinkered with a model they had early access to and recalled that “*you can identify some gaps [in capability] right off the bat.*”

While some designers welcomed the easy access to ChatGPT or tried out the GPT playground as a means to familiarize themselves with the “base” LLMs, participants recognized the necessity of tinkering with the adapted models. To gain access, designers either had to keep burdening the engineers or wait until a test version of the product is launched. P3 shared that “*The only way we would have [to tinker] is using the [product] online and play around with what [the team] did.*” P10 expressed frustration at this workflow: “*You want to be able to play with [the model] yourself and understand what the user experience is like. And I can’t play with it.*”

Some designers took the initiative to seek out new tools to tinker with and adapt models—currently, these tools are mostly limited to either programming with APIs or playground interfaces with many technical developer settings. However, usage of those tools did not persist. P1 tried various tools within and outside of their company and did not find them to be designer-friendly: “*[The tools are] still kind of technical, a lot of [designers] don’t realize how parameters work. Like how does temperature work?*” Others, such as P4, did not find the tools well-suited for their use case: “*I haven’t seen anything that feels like it makes it really easy to make small changes to a [system] prompt and then run the same set of queries over it and see whether it makes a difference.*”

Taken together, we envision adaptation and tinkering must be tightly coupled for designers to work with adapted LLMs within their design process. This includes being able to easily create, test, and iterate on versions of adaptation, and having this workflow be integrated into their design environment to reduce friction and eliminate dependence on engineers. Moreover, as noted in Section 2.2, some approaches to adaptation demand technical skills designers typically do not acquire in their training, and also do not fit within the tight feedback loops of the design process due to high data and compute overheads. Thus, we consider prompt-based adaptation methods to be most ideal for designerly adaptation. This broadens participation for designers while still allowing for modification of many aspects of model behavior.

3.3 Summary: A Characterization of Designerly Adaptation

We present three characteristics of designerly adaptation through several key insights drawn from our formative study’s findings. First, not all forms of adaptation can be considered as designerly adaptation. Designerly adaptation **should not demand a high degree of technical expertise in AI**—instead, designers should be capable of and prepared to conduct it with their current skillset and training. One promising approach to designerly adaptation, then, is to author system prompts with natural language. Second, designerly adaptation should **take advantage of designers’ unique expertise and perspectives** to inform model behavior. This may include incorporating user research into the system prompts. Third, **tinkering should have a major role in designerly adaptation**, encouraging tight feedback loops of creation, testing, and iteration that align with feedback loops in the broader design process.

4 CANVIL: A TECHNOLOGY PROBE FOR DESIGNERLY ADAPTATION

In light of our formative study, we introduce CANVIL,⁵ a technology probe for designerly adaptation in the form of a Figma widget. We first outline our design goals, which we ground in our formative study’s findings. We then walk through CANVIL’s user interface and implementation.

4.1 Design Goals

Our design goals, informed primarily by insights from our formative study and supported by our literature review, guided *why* and *how* we built CANVIL. They are as follows.

DG1: Support designerly adaptation via system prompting.

Our formative study revealed that some designers were already experimenting with system prompting in their design workflows (Sections 3.2.1 and 3.2.2). System prompts are also an appropriate medium for architecting UX—they shape a model’s behaviors across all or a specified group of user inputs. We also note that among the diverse techniques for adaptation (see Section 2.2), system prompting is conducted in natural language, making it accessible to designers, many of whom lack a technical background.

DG2: Leverage abstractions and environments designers are already familiar with.

Designers who want to be more involved in adaptation can feel unsupported due to existing tools (e.g., calling APIs programmatically) not aligning with their established workflows and mental models. Indeed, we saw in Section 3.2.3 that designers sought out new tools for adaptation but discarded them after a while because they were too technical or did not match desired use cases. Given that designers prefer to stay in one tool of their choice (e.g., Figma) for most stages of the design process [29], we hypothesize that tools for designerly adaptation should be tightly integrated with design tools and leverage common abstractions within those tools (e.g., layers, components, frames) to better align with designers’ mental models.

DG3: Allow for user research to inform model behavior.

When an LLM is integrated into a user-facing application, it becomes part of a sociotechnical system embedded in the deployment context [84]. Designers are well-positioned to understand this context and leverage their understanding for LLM adaptation from working closely with users or user research data (Section 3.2.2). Therefore, we invite designers to consider the user and social factors surrounding the UX at hand *in tandem with* the technical capabilities of the model. That is, we empower designers to adapt model behavior with user research insights.

DG4: Provide opportunities for collaboration.

UX is a highly collaborative practice [20, 29]. In our formative study, we saw that designers collaborated closely with not only other designers, but also product managers, software engineers, data scientists, and more. All these roles can contribute to adaptation. Moreover, not all desired model behaviors can be realized with prompt-based adaptation alone—for example, connecting an LLM to a knowledge base will likely require collaboration with a developer or data scientist (Section 3.2.1). We therefore design our system to afford collaboration with diverse technical and non-technical stakeholders.

DG5: Enable tightly coupled model adaptation and tinkering within the design process.

Designers found model tinkering highly valuable in our formative study as it allowed them to better understand LLMs as a design material—how they behave, what they are capable of, and where their limitations are. This aligned with prior work on designers working with AI models more generally [30, 91]. Yet, our formative study indicates that designers currently

⁵The name “Canvil” is a portmanteau of “canvas” and “anvil.” We envision CANVIL to be a metaphorical anvil by which LLM behavior can be shaped within design canvases.

had limited to no involvement in adaptation, nor access to tinkering with adapted models. Even if some limited opportunities for tinkering exist, they would require designers to leave their established workflows to seize those opportunities. We thus aim to incorporate tinkering and adaptation seamlessly into the design process.

4.2 CANVIL as a Probe

We envision designerly adaptation as a new opportunity for designers to contribute to model adaptation efforts. To investigate whether and how this new practice may be included in existing design workflows, we designed CANVIL as a *technology probe*.

Commonly used in contextual research in HCI [35, 42], a technology probe is an artifact, typically in the form of a functional prototype [39], presented to the user “not to capture what is so much as to inspire what might be” [56]. That is, probes offer one instantiation of tooling and/or interaction techniques for a domain to better understand phenomena within that domain. Hutchinson et al. [39] state that technology probes have three goals: the *social science* goal of understanding users in a real-world context, the *engineering* goal of field-testing the technology, and the *design goal* of inspiring new technologies. We map these three goals onto our objectives with CANVIL:

- *Social science*: understand how designers’ engagement with model adaptation impacts their work on LLM-powered user experiences through a structured design activity in Figma.
- *Engineering*: develop and launch a Figma widget that connects to OpenAI’s LLMs and allows them to be adapted via system prompting from within Figma.
- *Design*: encourage reflection on designerly adaptation as a UX practice and inform future tools to support it.

4.3 User Interface

The CANVIL interface resembles an interactive card. The card itself is separated into two areas: the *Main Form* and *Playground Area*. When a user selects a CANVIL, a property menu is invoked that can open up additional panels for styling, response generation, and settings. CANVILs can be freely placed on and moved around the Figma canvas, allowing model tinkering to take place in close proximity to relevant designs. CANVILs can also interact directly with designs by reading inputs from and writing model outputs to their text layers. We detail each of CANVIL’s features in this section and connect them with our design goals.

4.3.1 Main Form. The Main Form provides a means of authoring a system prompt (**DG1**) in a structured manner via a multi-field form. Unlike prior systems that offer more or less an open text field for system prompting [64, 72, 73], we chose to enforce structure because it provides mental scaffolding to reason about the system prompt in a UX context from multiple facets (e.g., *with whom* will the LLM interact, and *how* should the LLM meet their goals?), thus providing more opportunities for designers to integrate user context into the LLM (**DG3**). Additionally, designers can collaboratively author system prompts (**DG4**) by each working on a particular field and collectively deliberating afterwards. Breaking down the system prompt into smaller units also allows for more fine-grained experimentation (**DG5**)—designers can copy a CANVIL and tweak a specific field to compare how that change impacts model behavior.

Below are the fields, with a brief description of each, in the Main Form. The field titles (**in bold**) are always visible on the interface, while the field descriptions can be accessed by hovering over an info icon beside each field title.

- **Model profile**: High-level description of the model’s role, character, and tone.
- **Audience setting**: Persona or descriptions of user(s) who will interact with the model.



Fig. 1. An overview of the CANVIL interface. **A:** A blank CANVIL with its property menu invoked. The property menu has options for styling (1), model response generation (2), and model settings configuration (3). The *Main Form* (4) contains text input fields for structured authoring of system prompts. The *Playground Area* (5) allows users to quickly test inputs and view model outputs. **B:** A CANVIL with some copies styled with pre-set color options in the property menu. Like any other native Figma object, CANVIL allows for stateful duplication. **C:** CANVIL supports collaboration by default. Here, we see Figma users collaboratively authoring a CANVIL titled “Yoda impersonator.”

- **Core instructions:** Logical steps for the model to follow to accomplish its tasks. Specify input/output format where applicable.
- **Guardrails:** How the model should respond in sensitive or off-topic scenarios, including any content filters.
- **Example inputs/outputs:** Examples to demonstrate the intended model behavior.

We derived these fields from synthesizing system prompting guidelines offered by technical tutorials [57, 66] as well as NLP literature [21]. We note that our fields are just one possible way to structure a system prompt, and there may be some overlaps between the fields. As discussed in Section 2.2, no “gold standard” currently exists for prompt authoring, so we chose to follow the current recommended guidelines when designing the Main Form.

4.3.2 Playground Area. Below the Main Form, we provide a Playground Area as an easy way to send user inputs to the model and test model responses (**DG5**) within CANVIL. The designer may test on the same CANVIL multiple times or duplicate one with its entire state and test different tweaked versions (Fig. 1B). Designers are likely to find stateful duplication intuitive as it is available on all native objects in the Figma canvas (**DG2**).

4.3.3 The Generate Panel. To generate a response from a model adapted with the system prompt authored on the Main Form, the user selects the “Generate” option from CANVIL’s property menu, which takes them to the Generate Panel. The panel has two modes: *Playground* and *Design*. Both modes contain an option to copy the raw prompt to one’s clipboard so it can be tested in a separate environment (e.g., a Python notebook during collaboration with a data scientist), if desired.

Playground Mode. The Playground Mode (Fig. 2A) is invoked when the user selects “Using playground” from the dropdown on the Generate Panel. This mode instructs CANVIL to read user

input from the Playground Area and write its response back to the Model Response area. This mode is the default mode in CANVIL.

Design Mode. The Design Mode (Fig. 2B) is invoked when selecting “Using design” from the dropdown. In this mode, CANVIL navigates the design layers on the user’s Figma canvas, reading text inputs from a specified layer(s) from those designs, and writing model responses to a specified layer(s). This mode leverages the hierarchical layer structure of Figma designs (DG2) and implements the “input-output” LLM-interaction proposed by Petridis et al. [72].

The user can directly select a layer from their Figma canvas and use the “Set read layer(s)” button to bind it as CANVIL’s input. This allows CANVIL to retrieve and use the text from the bound layer as user input. If the user has inputs from matching layers⁶ from the same screen, they can check the option to include them as input, and CANVIL will read from those layers accordingly. Similarly, the user can select a layer to which the model writes its response. However, when implementing the checkbox for writing to multiple layers, we realized that writing the same output to multiple locations on the same screen is rarely meaningful for designers. As such, we designed the write layer checkbox to search for matching layers *across* screens for simultaneous updates in multiple screens along a user flow, ensuring content consistency within a particular matching layer.

4.3.4 The Settings Panel. The Settings panel (Fig. 2C), accessible through the “Settings” option from CANVIL’s property menu, contains some basic model settings for the user to configure, along with a field for the user to enter their OpenAI API key required for response generation. We distilled the list of settings in the OpenAI API to four (model selection, temperature⁷, maximum generation length, stop words) that may be useful to non-AI experts such as designers. The “Update Settings” button saves the settings to CANVIL’s state, which is preserved when the CANVIL is duplicated.

4.4 Implementation

CANVIL is a Figma widget⁸ implemented in TypeScript using the Figma API.⁹ A Figma widget differs from a Figma plugin¹⁰ by its collaborative nature. A widget is available to all users of the canvas that it is placed in, and maintains a common state that supports multi-user editing by default. Users can interact with widgets just like any other native object on the Figma canvas, including moving, duplicating, and styling. In contrast, Plugins are local to an individual user. The collaborative affordances of widgets align well with DG4, so we implemented CANVIL as a widget.

Upon the user selecting “Generate,” CANVIL prepares a system prompt using the text written on the main form. Each field in the form is converted to markdown format and is packaged up in ChatLM¹¹ for added prompt parsability. Our prompt template is available in Appendix B. The populated template is sent as a system prompt to an OpenAI Chat API endpoint with settings specified in CANVIL’s settings panel. If generation was triggered in Playground Mode, any text in the Playground Area will be sent as user input to the model. If generation was triggered in Design Mode, Canvil searches for the read layer(s) specified in Design mode on the user’s current Figma canvas, retrieves the text within those layers, and sends them off to the API endpoint as user input.

⁶We consider two layers as “matching” if they both have the same name and are of the same Figma layer type. Matching layers are common in designs with related information split up across different UI components. For example, a chat UI may have many matching layers that collectively contain one user’s dialogue across multiple conversation rounds.

⁷We rename “temperature” to “creative randomness” to provide a more descriptive name for those not as familiar with LLMs (confusion over the temperature parameter was raised in our formative study—see Section 3.2.3).

⁸<https://www.figma.com/widget-docs/>

⁹<https://www.figma.com/developers/api>

¹⁰<https://www.figma.com/plugin-docs/>

¹¹<https://learn.microsoft.com/en-us/azure/ai-services/openai/how-to/chatgpt>

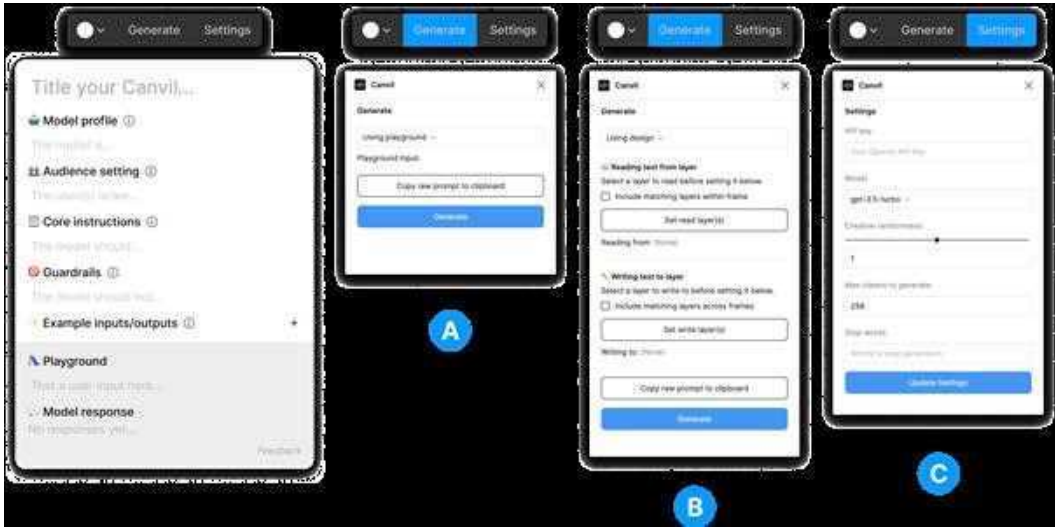


Fig. 2. The “Generate” and “Settings” options in a CANVIL’s property menu can lead to three panels that appear alongside the CANVIL itself. **A:** *Playground Mode* for response generation, where the input is read from and written to the CANVIL’s *Playground Area*. **B:** *Design Mode* for response generation, where the input is read from and written to design(s) on the Figma canvas. **C:** Settings for selecting and configuring the LLM.

CANVIL is compatible with both the Figma design editor and the FigJam whiteboarding tool. All features have the same behavior in both environments, except that the Design Mode for generation is not available in FigJam because of FigJam’s inability to access and edit design elements.

5 DESIGN STUDY

With CANVIL as a technology probe, we conducted a task-based design study with 17 participants organized into 6 groups. The study was conducted on a per-group basis; each session was 90 minutes in length. Our study investigated the following research questions:

RQ1. Implications of adaptation: How does engagement with designery adaptation impact design workflows and outputs in the context of our study?

RQ2. Adaptation at large: What are designers’ attitudes toward designery adaptation beyond the context of our study?

5.1 Participants

We recruited our participants from two channels. First, we distributed study invites to designers via email, professional interest groups, and word of mouth at a large technology company. Some of these invitees took part in our formative study. We also snowball sampled by asking our invitees to refer us to other designers they work with who may also be interested in participating. From this channel, we only selected designers with prior experience working on LLM-powered products and features. Second, we sent study invites to a Slack workspace for HCI and design maintained by a large, public academic institution in the United States. The population in the Slack consists primarily of design students and early-career designers. From this channel, we only selected those without any experience working on LLM-powered products and features. Our goal of recruiting from these two channels was to capture potential disparities that may arise in our findings hinging on prior experience working with LLMs.

Invitees first filled out a screening form with information on demographics, professional background, prior exposure to LLMs, and group member preferences. We then organized all candidates from the technology company into groups based on member preferences and availabilities, and did the same for candidates from the academic institution. We left recruitment open for both channels as we conducted the studies and stopped when we reached data saturation. In the end, we had 6 groups (3 groups from each channel) with 17 participants (8 from the technology company and 9 from the academic institution). Five groups were of size 3 and one of size 2. All participants were based in the United States. Participant and group details can be found in Table 2 in Appendix C.

All study sessions were recorded and transcribed. We sent each participant a \$75 USD gift card as an honorarium after the study. This study was approved by the Institutional Review Boards of all organizations involved.

5.2 Study Design

Our task-based study design was motivated by contextual inquiry [9] due to its ability to elicit rich information about participants’ work practices and processes. We conducted our study virtually over videoconferencing software and Figma. We opted for a group study design to better emulate the team-based environment in which many designers now work [29]. A group study may also help uncover more insights about enabling collaboration (**DG4**) than prior individual design studies about AI-powered user experiences [28, 30, 73, 91].

5.2.1 Setup. The following instructions for the study’s design task were provided to all groups:

You are all designers on a product called Feasto. Feasto aims to increase users’ enjoyment of food. The Feasto team is scoping out a new feature called the 3-course meal planner, which allows users to get suggestions for 3-course menus they can cook by simply listing out some ingredients they have. The team agrees that large language models (LLMs) are a promising technology to power this new feature. Your task is to design the UX for the area in which users will see and interact with the suggested menus.

We assembled these instructions cognizant of the fact that this was a time-constrained study, and we wanted participants to specifically focus on the area of the interface where users interact with an LLM. To reduce design overhead unrelated to our research questions, we provided starter UIs for participants to work with, along with basic UI components such as text, buttons, and sticky notes (Fig. 3B). If participants had an idea but did not have time to execute it, we encouraged them to describe it on a sticky note next to their designs.

To better probe *research-informed* model adaptation—that is, adaptation across varying user contexts informed by user research (**DG3**)—we created descriptions for three hypothetical user groups of this new Feasto feature based on users’ geographic region: west coast of the U.S., Turkey, and India. These descriptions are not meant to act as user personas, but rather high-level sketches of the customs and preferences that may be prevalent in the region. We crafted the user group descriptions to vary along three key dimensions (assuming everyone used Feasto in English): **dietary restrictions**, **access to ingredients**, and **menu style preferences**. Definitions for these dimensions, along with the full user group descriptions, are available in Appendix D.

We provided one blank starter UI with some example user inputs and one blank CANVIL per user group. Participants were invited to vary the user experience between user groups as much or as little as they saw fit. We also encouraged participants to use CANVIL to adapt an LLM and test its behavior as they designed.

A Figma file for each study group contained all the materials described above. Within the file, we created separate canvases for each participant to act as individual workspaces, each with its

own copy of the materials (Fig. 3). We also had a shared canvas for introductions and instructions before the task and collectively debriefing afterwards.



Fig. 3. The setup for an individual participant’s canvas in our study’s Figma file. **A:** Informational packet containing descriptions of three user groups residing in North America (primarily west coast of the U.S.), the Middle East (primarily Turkey), and Asia (primarily India), respectively. **B:** Starter UIs for Feasto’s 3-course meal planner with example user inputs to lower the barrier for testing model responses, along with basic UI elements such as text and buttons. **C:** Blank CANVILs for participants to adapt LLMs.

5.2.2 *Procedure.* Our 90-minute study was divided as follows.

Introduction (20 minutes): First, all participants introduced themselves to others in the group. The study facilitator then gave a demo of CANVIL, covering all features described in Section 4.3 using a pre-filled CANVIL. The facilitator also described the design task and answered any clarifying questions from participants.

Design task (40 minutes): Participants spent 40 minutes on the design task and were asked to consider at least two of the three user groups provided. Participants were encouraged to spend 10 minutes authoring a CANVIL and another 10 minutes on UI design per user group. Some participants who had remaining time designed for all three user groups.

Group interview (30 minutes): Participants first filled out a brief usability questionnaire about CANVIL before gathering in the shared page of the Figma file. They were asked to copy their CANVILs into the shared space and also their designs (if desired) to share with the group. The facilitator then led a semi-structured interview that asked participants to reflect on their experience adapting models with CANVIL, CANVIL’s collaborative capabilities, and how they see adaptation fitting in with their own design practice. The facilitator ensured that each participant had ample opportunity to express their thoughts in the group setting, and also encouraged dialogue between participants.

5.3 Data Analysis

We conducted a qualitative analysis of transcriptions and Figma canvases (including authored CANVILs), as well as a quantitative analysis of feedback from CANVIL’s usability questionnaire.

For our qualitative analysis, the first author took a hybrid inductive-deductive approach to coding the group interview portion of the transcriptions from the study. This process started with an open coding round in which high-level themes were generated, followed by subsequent rounds of

thematic analysis via affinity diagramming in which themes were broken down into sub-themes. This approach was taken because new subtleties and complexities emerged from our initial codes as coding progressed due to the diverse approaches observed in our study as well as participants’ group discussion dynamics. The codes and themes were discussed and iterated on with research team members at weekly meetings. Additionally, whenever participants made references to content within their Figma canvases (e.g., their designs and/or CANVILs), the first author took screenshots of those references and linked them to transcript dialogue. Summary memos were then written for our high-level codes and presented alongside relevant screenshots.

CANVIL’s usability questionnaire followed the standard template for the System Usability Scale (SUS) [12, 94] and consisted of 10 questions, each with five response options for respondents from Strongly agree to Strongly disagree. We computed a SUS score using methods outlined by Brooke [12] for each participant and subsequently computed a mean score and standard deviation.

6 RESULTS

Our quantitative analysis showed that CANVIL had a mean SUS score of 69.94 (std = 12.18), meaning its usability was “above average” [94]. In this section, however, we focus on the qualitative insights on designerly adaptation from our design study. We specifically showcase the implications of satisfying CANVIL’s design goals (Section 4.1) on design workflows and outputs. Our results from designers without prior experience working with LLMs did not differ noticeably from those with experience, except that the latter drew more connections between adaptation and their past model tinkering workflows. We present text that participants wrote in CANVIL as *purple and italicized*.

6.1 Authoring System Prompts as Part of Design Workflows

6.1.1 Research-Informed System Prompting as a Design Activity (DG1, DG3). When authoring system prompts in CANVIL (**DG1**), designers frequently referenced the provided user research documents. It is through this process that they embedded user context—e.g., varying lifestyles, customs, preferences—into system prompts (**DG3**). For example, in P2’s CANVIL for the American user group, they wrote under Audience Setting that the model is serving users who *like diverse cuisine but care about the environment and sustainability and are health-conscious*. Designers also adjusted their prompts between user groups in attempts to create more customized and meaningful user experiences. In the CANVIL for the user group from India, P4 wrote that *The model should use Indian terminologies to describe the recipe. Eg: eggplant is brinjal in India*. P5 experimented with model variations *within one user group*, choosing distinctly different personalities for each model. For their Indian user group, they populated one CANVIL’s Model Profile field with *The model is a head chef of a 5 star restaurant situated in New Delhi. It is a busy day for the restaurant and the chef is low on time.* and another with *The model is a mother who is helping her son cook quick meals in hostel*. In the end, they noted that *“the models did very well”* in taking on these different profiles.

In particular, designers used the Guardrails field in CANVIL to address potential violations of users’ dietary preferences and restrictions, along with model misuse. For example, P12 used information provided on the Turkish user group to create the following guardrail: *The model should not include recipes with pork or alcohol and must respect the fasting period of Ramadan by suggesting suitable pre-dawn and post-dusk meals*. A few participants noted that some user groups may require more strict model guardrails than others. P15 identified a subtle but key requirement between two user groups while authoring their CANVILs:

“I wanted to highlight that the model could take many more liberties with the recipes that it was giving [to the Turkish user group], but it couldn’t take more liberties with the ingredients. It could be very loose with: try this, try this with this, but never like crossing

the boundary of the dietary restrictions. Whereas with the [American] one, it'll take it into account, but it's not gonna mar their religious practice.” [P15]

Designers sought to address user needs through combined efforts in prompt authoring and UI design. For example, P15 provided alternatives via buttons to support more flexible user input of ingredients going into the model. P8 described their UI design in response to observing the limits of what can be achieved via writing system prompts: *“Sometimes even in the instructions that I gave to CANVIL, it wasn't really reflecting that [desired] granularity until I pushed it further. In my design I ended up putting a little textbox area where people can specify how detailed they want the instructions.”* Fig. 4 contains some examples of designers' UIs from our study.

In short, the structure provided by prompt authoring interface of CANVIL is compatible with designers' reasoning about user needs and preferences based on user research. CANVIL supports this reasoning process to inform both the system prompts and UI design in an integrated fashion, and makes authoring system prompts a natural part of design activities.

6.1.2 Tinkering Allowed for Deeper Reasoning of User-LLM Interaction (DG2, DG5). CANVIL's integration in the design environment (DG2) allowed designers to consider model behavior and user interaction simultaneously. Many designers iterated multiple times on their system prompts (DG5) until they were satisfied about the adapted model. P3 reformatted the output to better suit their existing UI: *“the first run was a paragraph that I felt like was really hard to read, so I added some core instructions saying give me a numbered list.”* P13 shared that their model was repeating the same ingredients for each course, so they *“tweaked the level of detail and the recipes to add more variety.”* P11 discovered that, in general, *“stating [instructions] in the positive instead of the negative”* yielded better results for their envisioned experience.

Designers' tinkering with the adapted model not only helped them iterate on their system prompts, but also allowed them to more deeply reason about user interactions with LLMs and reflect on the *whys* of UI design. For P14, grappling with the Example Inputs and Outputs field in CANVIL prompted reasoning about the optimal interaction pattern to design with:

“The example inputs and outputs were a little bit hard for me to think about, cause I was wondering for the output, is it just the recipe? Or would it be more of a conversation, like oh, do you have dietary restrictions? Do you have any XYZ preferences? Like there's some logic that goes into asking those questions and I was wondering which one should I think about first versus later.” [P14]

Tinkering with the adapted model often led to evolving of or experimenting with UI ideas. P17 considered different interaction patterns for their interface—a chat-based interface versus a form-filling GUI—after discovering how sensitive LLMs can be to prompts. P4 mentioned that they started off with *“a specific user base in mind and I wanted a specific tone,”* but the design of the UI became clearer after they saw an ideal output after multiple iterations: *“My design direction changed when I saw the output. I iterated multiple times and what I like the best about this [response] was that it was short and [ideal] for scrolling in a screen. I tried that out [in my new UI] and it worked pretty well.”* Examples of quoted participants' designs can be found in Fig. 4.

Interestingly, a few designers wanted a degree of separation between UI work and model tinkering. P1 shared that they found it *“a bit hard to juggle between CANVIL and [the UI] at the same time,”* especially when the output is incompatible with their design settings: *“What if the text is really long and then I have to play with auto layout?”* Therefore, P1 preferred first tinkering with the model using the Playground Mode. P8 also agreed that having CANVIL inject outputs directly into text boxes can be *“a little scary [...] people don't wanna actually commit [responses] to text boxes*



Fig. 4. Examples of UIs designers created for Feasto’s 3-course meal planner during the study.

sometimes.” Past work considers integration between models and UI designs as desirable [72, 73, 91]. Our results encourage providing designers with more choices and control over such integration.

6.2 Designers Envisioned Collaborative Workflows with Designerly Adaptation

6.2.1 Collaborative Uses of CANVIL in Design Teams (DG4). The design task in our study was an individual activity because we expected collaborative efforts to begin after designers had made some individual attempts at adaptation and designed with the adapted model [29]. Indeed, when reflecting on CANVIL’s collaborative capabilities (DG4), designers thought the workflow matched their own experiences. P8 did not consider a “divide and conquer” authoring approach—where each team member is responsible for one CANVIL field—as necessary unless the team was under a tight time constraint, and instead saw more potential in a “tinker and unite” approach: “Since it doesn’t take too much time to generate a response, I feel like I would lean towards, let’s all try different things and see how

we can use this tool to get the best response." P8 added that in order for this approach to work, some guidelines should be set for collaborators *"so that all of our responses are consistent, like everyone has the same Audience Setting and [uses] the same kind of wording."* P4 agreed and suggested initial brainstorming sessions for collaborators so that they could *"find a way to come to common grounds for all these [fields]."* P6, after hearing P4's suggestion, noted that using CANVIL within FigJam may be useful *"for ideation or brainstorming"* before bringing more polished CANVILS into Figma.

On the other hand, some saw potential in the "divide and conquer" approach, especially when expertise in a design team may be distributed. P7, who specialized more in visual design, said that they were *"struggling a little bit with like how to prioritize all the content, and I feel like that would be specialties a content designer would bring in."* P8, who initially preferred to "tinker and unite," agreed that it would be valuable to also leverage distributed expertise: *"In a design team, there might be someone who knows a user persona the best, and they can be assigned to Audience Setting. Then you have content designers on maybe example inputs and outputs."*

6.2.2 Collaboration and Knowledge Sharing Afforded by CANVIL (DG2, DG4). Many designers commented on how CANVIL, as a widget integrated into Figma's design environment (**DG2**), afforded collaboration (**DG4**). P5 appreciated that they could leverage Figma's built-in collaboration features: *"If I see my fellow designer's CANVIL, and if I want to change something then and there, I can drop a comment on it just like a normal component in Figma, which we've been doing in our everyday design work."* P10 shared that their team relies on a spreadsheet to keep track of system prompt iterations and working in a canvas environment would be a significant improvement.

In particular, participants saw potential for more effective knowledge sharing about adaptation with CANVIL. P10 commented that: *"You could have a master CANVIL and then you could make copies, and [others] can then do their own interpretations."* P11 agreed and added that seeing iterations on a canvas can help find inspiration in others' work: *"I think anytime you line up different iterations together, you notice: ohh that person, did you know they had that approach? That's a good idea. And I'm gonna try that over here. I think it really is an aid to experimentation."* We observed other instances of knowledge sharing as well when designers viewed others' CANVILS. For example, P4 noted that they were inclined to consider more dimensions for their system prompt after seeing P6's work: *"[looking at P6's CANVIL] made me thinking about timers and Hindi slang."* Some also realized new capabilities of LLMs by looking at others' prompts and outputs—P1 shared that *"I didn't realize at first that you can actually make the [LLM] generate multiple recipes, just like what P2 did."* P1's groupmates (P2 and P3) were also intrigued when they saw that P1 had used one CANVIL to generate example inputs for another CANVIL to use. These social and collaborative affordances differentiate CANVIL from prior systems for empowering designers to tinker with AI [15, 73, 91].

6.2.3 Collaborating With Non-Design Stakeholders via CANVIL (DG1, DG4). With system prompt authoring as the primary interaction, CANVIL (**DG1**) ensures easy authorship and sharing within a team (**DG4**), even across domain boundaries. Many designers thought that CANVIL was simple and intuitive enough to be used by not just designers. Consequently, P2 saw CANVIL as a useful boundary object [89]: *"I can see from a product manager's perspective that they would love to play around with the prompts, and it would probably help the designer explain their design choices. I feel they would find more common ground because they both used a similar tool."* P6 agreed that product managers (PMs) have perspectives and expertise to contribute to prompt authoring. Designers also saw potential for deeper collaboration with data scientists and other technical stakeholders. P11 commented that the "Copy raw prompt to clipboard" button in Generate Panel (Section 4.3.3) can allow for direct handoff of system prompts: *"[The button] is a way of exporting that so a data scientist can come along and say sure, let me plug that into code."* Even if designers were unable to achieve the desired model behavior themselves, P17 thought CANVIL was helpful in specifying desired

changes: *“If I want the model to respond in this way versus that way, just having something tangible to show engineering partners where the tweak would need to be, would be helpful. And I think [that’s] obviously easier with CANVIL.”* P15 believed that rise of natural language as a shared representation can allow for more transparent and balanced information flow between disciplinary boundaries:

“I think on the designer side, there is apprehension about [AI] being in different skill set. The [technical] teams just don’t really embrace designers, cause this is ‘their’ skill set. They’re gonna do it quicker and better, and that’s probably true in almost all circumstances except natural language. And except when it comes to an intuitive experience. So it’s about making the teams meet each other as opposed to one team being more reticent than the other.” [P15]

Designers also acknowledged that designerly adaptation may only be one piece of the larger puzzle to steer an LLM’s behavior and integrate it into a product. Some desired changes, such as factual grounding and connecting to external knowledge bases, may still need to be left to technical teams. P12 even saw factual grounding as a prerequisite to designerly adaptation: *“because everything hinges on you being able to get the model specificity correct.”* Both P12 and P14 wanted CANVIL to be able to connect to other models built and maintained by their own teams, as the behavior of unadapted OpenAI models may be too generic to use as an effective design material. P14 comments: *“I think linking to the vanilla ChatGPT model isn’t specific enough. If there is a way to somehow have CANVIL link to the devs’ [models] while I’m designing and I’m able to see what type of experience and what type of response our users are getting, I think that would be super helpful.”*

While we currently offer only three OpenAI models to use with CANVIL (GPT-3.5-Turbo, GPT-3.5-Turbo-16k, GPT-4), more may be added with lightweight engineering as the widget is communicating with the model via API endpoints. As such, we can envision future support for more model families, including teams’ custom models.

6.3 Designerly Adaptation at Large

6.3.1 Integrating Adaptation into Design Practice. Designers saw great value in engaging with adaptation and saw direct paths to application in their own design practice beyond the study. P10, who has extensive experience working on AI-powered products deployed to users worldwide, said that adaptation has traditionally been difficult: *“We had teams of people training models and nudging the technology to align with [user personas].”* Having experienced adaptation of LLMs via CANVIL, they shared that *“I can see this being something that would enable [adaptation] to actually happen in a way that’s much more practical than taking Python classes, which I’ve done.”* For P13, who works on a product with enterprise and consumer versions, adaptation can help set more detailed product requirements where necessary: *“I could see [adaptation] being really helpful, being able to prototype and build separate generative models for enterprise customers and then to work more closely with them to tune and add requirements.”* P16 considered adaptation to be a useful exercise for user empathy: *“for [Audience Setting] I just tried to put myself in the mind of someone who’s using this and say, I’m really good at following recipes, but have a variety of dietary preferences and restrictions.”*

Some participants pointed out that designers should be prepared to carefully navigate challenges of adaptation that may arise in practice. P11 reflected on the balance between specificity through adaptation and breadth of audience: *“I wanted to avoid bias in these [models]. There’s that balance between, having the profile of the model be specific enough so that it’s relatable [...] and making technology for everybody. If you try to make it too generic, it’s just gonna be bland. So we have to be careful.”* P15 pointed out that adaptation may not account for all user needs and preferences: *“in terms of the normative sense, it would be fantastic. But feasibly though, there are so many different things that you need to take into account, like even length of language.”* These complexities highlight

the broader social and ethical factors surrounding designerly adaptation to confront as designers integrate it into their own practice.

6.3.2 Designerly vs. End-User Adaptation. Prior work found that designers were naturally inclined to provide end-users with more controls for customization of their AI-powered user experiences [30]. Some designers also did the same in our study and reflected on the interplay between designerly and end-user adaptation. P15, who discussed the complex factors of adaptation in Section 6.3.1, said they envisioned a more feasible approach to be designers delegating adaptation to end-users past a certain point: *“If we could put in a Venn diagram of all of the different needs from all over the world, seeing what the more central options are, the really interesting piece here is having users be able to make that [adaptation] decision themselves.”* P10, after interacting with CANVIL, started thinking about similar tools for end-user adaptation: *“I thought [CANVIL] could be a tool, yes, for us content designers, but could we adopt this for individual users so they could tweak [the model]?”* However, they acknowledged that granting end-users complete control over adaptation may not be ideal either, and designers are responsible for setting certain constraints:

“In my experience with human beings, you don’t want to give them a blue sky. You wanna give them things they can create on their own and feel like they’re in control. I could see us using [CANVIL] to create something like 5 or 6 different [model] personalities that users around the world could leverage.” [P10]

P11 also found the idea of balancing designerly and end-user adaptation appealing, as they were concerned about model biases (see Section 6.3.1). They proposed having *“a preference or a setting or a dial based on your regional settings where [LLM behavior] could be modulated.”* With the rapid rise of LLM-powered user experiences, we invite practitioners and researchers to more deeply reason about *who* can be responsible for adaptation and *when* adaptation should happen.

6.3.3 Areas of Additional Support. Designers’ also identified several areas for improvement to better support designerly adaptation. For one, designers lacked a clear mental model of how the fields of CANVIL would impact the adaptation outcome, including how much detail is required in authoring the prompt. As a result, some designers wrote long, detailed instructions, while others kept their CANVILs sparse, and some were pleasantly surprised by how well the model handled minimal instructions. P6 further noted that the stochastic nature of the model was particularly challenging to work with when writing outputs to their designs: *“every time I generated the [response], I felt that they were different every time, so it was not easy to predict what the next [response] would look like.”* We note that current LLMs are known to be challenging to be precisely controlled through prompting, and there is a lack of transparency into (or even an established understanding of) how prompting impacts LLM behaviors. However, these are actively researched areas which can help improve the mental model of CANVIL’s users and its general effectiveness.

Additionally, some designers wanted to engage in finer-grained experimentation and iteration by only focusing on a specific field at once. P7, who wanted to iterate more on the Model Profile field, wondered if there was a way to *“decrease the size [of the other fields] and expand to view everything.”* We envision a modular future version of the tool where each field can be separated, such that a user can mix-and-match different fields to form a complete system prompt. However, before that, we may need to address the precise mapping between each field (and potential overlaps between them, as noted by some participants) to adaptation outcomes as discussed above. As mentioned in Section 4.3, our fields present just one possible structure for system prompts. The fields can perhaps be reconfigured to reduce potential overlap, or even dynamically generated based on the design task.

On a higher level, it would be irresponsible to assume that designers can walk away with a comprehensive understanding of model behavior after a few rounds of tinkering in CANVIL. While

observing a few informative output instances of model behavior aids the design process, formal evaluations ensuring comprehensive coverage of the user input space are crucial for production-ready systems. Thus, new evaluation tooling and processes that loop in technical stakeholders may be required.

7 DISCUSSION

Our findings shed light on possible workflows for designerly adaptation, promises of tools for collaborative AI tinkering, and implications of materiality on the social and collaborative practices of product teams. We discuss each below.

7.1 A Workflow for Designerly Adaptation

Drawing on the results from both our formative and design study, we now propose a workflow for designerly adaptation. Our proposed workflow consists of four steps:

- (1) **Understand deployment context through user research.** To orient adaptation, it is imperative to first understand the context in which users will interact with the LLM-powered system. This includes users' goals, needs, and pain points, along with customs and values that may affect their use of the technology. Those with expertise in user research methodologies should lead the execution of this step.
- (2) **Embed user research insights into system prompts, learning from examples where possible.** This carves out a direct path for user research to impact model behavior, as we observed in Section 6.1.1. Thanks to the collaborative nature of many modern design tools [29], there may be example prompts written by other designers available for reference, or templates to use as a starting point (Section 6.2.1). By leveraging collaborative affordances to share knowledge, designers can enhance their efficiency at adaptation over time.
- (3) **Co-evolve interface design and prompts.** As observed in Section 6.1.2, adaptation can supply new inspiration for UI designs and affordances. On the other hand, designers also tinkered with prompts to coax the model into providing outputs that fit into the constraints laid out by the designs being explored. We see the co-evolution of designs and prompts as a promising path forward, in which iterative tinkering with system prompts for adaptation shapes design choices, and vice versa.
- (4) **Share designs and adaptation efforts with the broader team.** Showcasing in-progress work through design critiques is already a part of the design process [28]. In our study, we found that sharing CANVILs helped envision new collaborative workflows with other designers, as well as communicating their perspectives and negotiating with technical stakeholders (Section 6.2.1). Following from Step 3, we thus believe that sharing designs *alongside* adaptation is critical for involving designers and leveraging their expertise for responsible development and deployment of LLM-powered systems.

Our proposal is not meant to constrain what workflows for designerly adaptation can possibly look like, but rather to offer a concrete entry point for practitioners and researchers to further explore and iterate on this new practice. We invite the community to experiment with this workflow in future practice and research.

7.2 Towards Collaborative Tinkering With AI

Our work highlights the promises of not only empowering designers to tinker with LLMs as a design material, but also *collaboratively* doing so. During our design study, designers proposed various collaborative workflows for system prompting with CANVIL, including a divide-and-conquer approach to gather expertise distributed across the team and a tinker-and-unite approach where

each designer tinkers independently before merging the results into a team version (Section 6.2.1). Additionally, designers benefited from seeing and learning from others' CANVILs and commented on more organized knowledge sharing and version management afforded by using CANVIL in Figma's multiplayer canvas environment (Section 6.2.2).

Despite promising opportunities, many tools that lower the barrier for AI tinkering (e.g., [15, 52, 54, 91]) were designed with individualized workflows in mind. Some, like Google's Teachable Machine [15], offer social features such as project galleries to showcase example projects, but affordances for collaboration remain limited. One reason may be technical constraints surrounding the collaborative updating of computationally heavy stages of large-scale training pipelines. The shift towards using large pre-trained models, and the ability to interact with these models via natural language, helps accelerate model adaptation and tightens feedback loops during tinkering. Consequently, novel interfaces, such as node-based editors, (e.g., [2, 4, 93, 104]), enable users to decompose large tasks by "chaining" together smaller prompt submodules. Node-based editors are conceptually appealing for collaboration [104]—collaborators may distribute work according to expertise and nature of the task within the submodule, and easily chain together their work. Few node-based editors, however, support multiplayer collaboration. We see significant potential in extending these tools along a collaborative dimension.

Besides technical constraints discussed, it can simply be the case that robust collaborative experiences are generally challenging to implement. We circumvented this in our work by building on top of the Figma API, which allows us to leverage Figma's built-in collaborative features by default. We thus encourage researchers and practitioners who wish to build collaborative tools to take advantage of existing collaborative platforms' developer APIs where possible, especially as these APIs become more richly featured.

7.3 Materiality and Sociomateriality of LLMs

Throughout this work, we depict LLMs as a design material to use materiality as a means of understanding, shaping, and applying this technology to tackle design problems. Yet, in collaborative settings, materiality's implications extend beyond the individual. Scholars use the term *sociomateriality* in recognition of materiality's tendency to shape, and be shaped by, organizational practices typically constituted as "social" (e.g., decision-making, strategy formulation) [49, 68]. For example, Orlikowski observed that the issuance of BlackBerry devices within a company led employees to obsessively check for new messages and send immediate responses [68]. The BlackBerrys' material properties—in this case, being able to receive and send messages on-the-go—reconfigured employees' social practices, which in turn shifted how they think and act with the technology.

In our design study, designerly adaptation allowed for exploration of LLMs' material properties through tinkering. As a result, designers proposed various UI affordances for enhancing users' interaction with the LLM-powered meal planner (Section 6.1.2) and adjusted the model's guardrails depending on differing dietary restrictions between user groups. However, grappling with the materiality of LLMs also demonstrated potential to reconfigure social practices within product teams. For example, designers informed us that they saw new avenues of collaboration upon interaction with CANVIL, which included "handing off" system prompts to data scientists by exporting prompts out of Figma, working with PMs to inform prompts with product requirements, and having a more concrete artifact to communicate desired tweaks to engineers (Section 6.2.3). Moreover, designerly adaptation itself may only be one piece of the broader adaptation puzzle. Certain capabilities such as storing external knowledge in model weights through fine-tuning cannot easily be unlocked through—and may even be a prerequisite for—designerly adaptation, paving the way for processes and artifacts that fundamentally differ from those used in tradition design handoffs [31, 48]. This

potential reconfiguration of teams’ collaborative dynamics establishes designerly adaptation as not only a means of exploring LLMs’ materiality, but also a sociomaterial practice.

The implications of this observation are twofold. First, sociomateriality argues that reconfigurations of collaborative practices upon interaction with a prominent new technology are *inevitable* [49, 68]. At the time of writing, frenzied excitement over LLM capabilities has launched an industry-wide race to embed them into products and product suites [71]. There is much yet to be discovered about shifts in organizational practices and the emergence of new ones in the midst of this race, so researchers in CSCW and organizational science should be attuned to emergent challenges. Second, addressing these challenges for practitioners and providing probes for researchers to study them may require new processes and tools. CANVIL is an early example of such a tool, but more are needed to tackle the multiplicity of open questions in today’s rapidly evolving AI landscape.

8 LIMITATIONS AND FUTURE WORK

Our design study, conducted in Figma, aimed to mirror real-world design activities [6], yet concerns about ecological validity may persist. User research in practice may differ in presentation and detail than in our study setup, which can impact how designers perform research-informed adaptation. Feasto, the fictitious app in our design study, applied LLMs to the universally relatable topic of food. Designers in domains with fewer broadly-shared experiences (e.g., accessibility), may require deeper collaboration with domain experts and thus face workflow complexities not accounted for in our study. A potential direction for future work, then, is longitudinal studies that use contextual inquiry to observe product teams throughout a full development lifecycle of an LLM-powered feature, focusing on key adaptation decision-making processes and the practitioners involved.

Our study, like any study that uses a probe, has results contingent on our probe’s features. For example, designers’ interaction with the Main Form—designed with recommended practices for system prompting [57, 66]—shaped their approach to adaptation, and changes to the form could impact existing results and reveal new ones. We mitigate this by presenting findings not tied to the Main Form, nor our design study task. Future research can build probes for designerly adaptation, distinct from CANVIL, to explore agreements with and divergences from our results.

Designers in our study also provided feedback on CANVIL that we can integrate into future work. These include breaking down the Main Form into sub-CANVILs and linking them together to assemble system prompts, offering support for multimodal models (e.g., GPT-4V¹²), and text formatting controls for model outputs. Finally, as mentioned in Section 4.4, CANVIL may also be used in FigJam. Future research could explore adaptation in early design stages, like brainstorming and ideation, through studies in FigJam.

9 CONCLUSION

In this paper, we introduced the practice of *designerly adaptation* to encourage designers to engage with LLMs as an adaptable design material when crafting LLM-powered user experiences. We first built up a characterization of designerly adaptation through a formative interview study with 12 designers. We then developed CANVIL, a Figma widget that operationalizes designerly adaptation by enabling designers to iteratively author, test, and share system prompts within Figma’s collaborative design environment. We used CANVIL as a technology probe to explore the integration of designerly adaptation in UX practice through a group-based design study with 17 designers. We observed numerous promising approaches taken by designers such as iteratively tinkering with different adaptation strategies, sensitizing the model to nuances in user needs, and

¹²At the time of our study, GPT-4V was not yet widely accessible via APIs, so the most advanced model available for use in CANVIL was GPT-4.

reasoning about interface affordances using research-informed model behavior; these approaches' promises were amplified once adaptation was embraced as a collaborative practice. Our work illuminates paths for new processes and tools to spotlight designers' user-centered perspectives and expertise for more responsible and thoughtful deployment of LLM-powered technologies.

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A FORMATIVE STUDY PARTICIPANTS

P#	Job Title	YoE	LLM Application Area	Education Background	Region
P1	Product Designer	6–10	Domain-specific Data QA	Visual/Industrial Design; Computing	Denmark
P2	Interaction Designer	6–10	Conversational Search	Visual/Industrial Design	Canada
P3	Principal Product Designer	6–10	Domain-specific Data QA	Visual/Industrial Design	U.S.
P4	Content Designer	6–10	Conversational Search; Domain-specific Data QA	Humanities	U.S.
P5	Principal Content Designer	6–10	Conversational Search	Humanities	U.S.
P6	Content Designer	1–2	Recommendation	Humanities	U.S.
P7	UX Researcher	3–5	Domain-specific Data QA	Visual/Industrial Design; Social & Behavioral Sciences	Ireland
P8	Product Designer	3–5	Creativity Support Tools	Visual/Industrial Design	U.S.
P9	Senior Designer	11+	Conversational Search; Creativity Support Tools	Visual/Industrial Design	U.S.
P10	UX Researcher	11+	Domain-specific Data QA	Social & Behavioral Sciences	U.S.
P11	Product Designer	3–5	Text Editing & Generation; Domain-specific Data QA	Social & Behavioral Sciences; Computing	U.S.
P12	Principal Content Design Manager	11+	Text Editing & Generation; Domain-specific Data QA	Humanities	U.S.

Table 1. Details of our participants (job title, years of experience in design, LLM application area of their product/feature, and education background before starting their current role) in our formative study.

B CANVIL SYSTEM PROMPT TEMPLATE

```
<|im_start|>system
```

```
# Context
```

```
[Model profile]
```

```
# Users
```

```
[Audience setting]
```

```
# Core Instructions
```

```
[Core instructions]
```

```
# Guardrails and Limitations
```

```
[Guardrails]
```

```
# Example User Inputs and Responses
```

```
[Example inputs/outputs]
```

```
# Final Instructions
```

You are the model described above. You will follow all instructions given to the model closely.

<|im_end|>

C DESIGN STUDY PARTICIPANTS

G#	P#	Prior LLM Design Experience?	Job Title	YoE	Education Background
G1	P1	No	Design Student	3–5	Visual/Industrial Design
	P2	No	Design Student	1–2	Visual/Industrial Design
	P3	No	Product Designer	3–5	Visual/Industrial Design; Computing; Information
G2	P4	No	Product Designer	1–2	Visual/Industrial Design; Computing
	P5	No	Product Designer	3–5	Visual/Industrial Design
	P6	No	UX Designer	1–2	Visual/Industrial Design
G3	P7	No	Digital Designer	1–2	Visual/Industrial Design
	P8	No	Accessibility & Product Designer	1–2	Visual/Industrial Design; Management
	P9	No	Design Student	1–2	Visual/Industrial Design; Computing; Information
G4	P10	Yes	Principal Content Design Manager	11+	Humanities
	P11	Yes	Principal Content Designer	6–10	Humanities, Visual/Industrial Design; Social & Behavioral Sciences
G5	P12	Yes	Senior Product Designer	3–5	Visual/Industrial Design
	P13	Yes	Product Designer	3–5	Visual/Industrial Design
	P14	Yes	Product Designer	3–5	Social & Behavioral Sciences; Computing
G6	P15	Yes	Content Designer	1–2	Humanities
	P16	Yes	UX Researcher	11+	Social & Behavioral Sciences
	P17	Yes	UX/UI Designer	1–2	Information

Table 2. Details of our participants (job title, years of experience in design, LLM application area of their product/feature, and educational background before starting their current role) in our design study. All participants were based in the U.S..

D FEASTO USER GROUPS

D.1 Dimensions of Variance

D1 Dietary restrictions: users in different locations may have varying dietary restrictions due to religious and cultural customs (e.g., Halal in Turkey, vegetarianism in India).

D2 Access to ingredients: based on their region, users may have easier access to some ingredients than others.

D3 Menu style preferences: some cultures may prefer precise and detailed menus and recipes, while others prefer looser guidelines or drawing from traditional cooking techniques.

D.2 User Group Descriptions

D.2.1 North America. A prominent percentage of users in North America live in the state of California. They enjoy a wide range of cuisines but many also consider themselves as health- and environment-conscious, adopting pescatarian diets to avoid heavy consumption of meat. Some have also reported nut allergies.

These users like to take advantage of the fresh fruits and vegetables that grow in the California sun, such as spinach, kale, citrus fruits, avocados, peaches, and berries. Due to their proximity to the ocean, many also enjoy diverse varieties of seafood.

When preparing food, these users tend to follow precise recipes.

D.2.2 Middle East. Turkey is home to many users from the Middle East. Because of the country's predominantly Muslim population, many users follow the Islamic dietary laws (halal) and enjoy traditional Mediterranean cuisine. They avoid pork and alcohol and also fast during the month of Ramadan, during which they eat only during specific hours.

These users enjoy access to a variety of Mediterranean ingredients like lamb, poultry, pita bread, olives, dates, and a range of spices like paprika, coriander, and cinnamon.

When preparing food, these users tend to treat recipes as loose guidelines rather than precise instructions.

D.2.3 Asia. A significant portion of users in Asia hail from India. Many of these users adhere to a vegetarian diet due to their Hindu beliefs, while others may consume white meat such as poultry or fish but rarely beef. Many also avoid onion and garlic during certain religious festivals.

These users enjoy access to a wide range of South Asian ingredients such as lentils, chickpeas, paneer (cheese); various earthy spices such as turmeric, cumin, and cardamom; and tropical fruits including papayas, guava, and mangoes.

These users rarely use written recipes, but instead rely on recipes and techniques passed on through word of mouth.