

# MenuCraft: Interactive Menu System Design with Large Language Models

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## Abstract

Menu system design is a challenging task involving many design options and various human factors. For example, one crucial factor that designers need to consider is the semantic and systematic relation of menu commands. However, capturing these relations can be challenging due to limited available resources. With the advancement of neural language models, large language models can utilize their vast pre-existing knowledge in designing and refining menu systems.

In this paper, we propose MenuCraft, an AI-assisted designer for menu design that enables collaboration between the designer and a dialogue system to design menus. MenuCraft offers an interactive language-based menu design tool that simplifies the menu design process and enables easy customization of design options. MenuCraft supports a variety of interactions through dialog that allows performing few-shot learning.

## 1 Introduction

Menus are widely used interfaces, providing users with an intuitive and efficient access to an application’s functions. Although menus may seem simple at first glance, creating a well-designed menu system is complex. This is because the number of alternative designs grows exponentially as the number of commands increases. By disregarding non-textual design factors such as size, saliency, and color, we can focus solely on the textual representation of menu systems. In this regard, the position of commands in the menu and the assignment of hotkeys are the two most critical factors in designing a menu system. Menus typically follow a consistent linear pattern, where command names are displayed on the left, and keyboard shortcut cues are aligned on the right (Giannisakis et al., 2022).

Since 1980, Human-Computer Interaction (HCI) researchers have been developing better tech-

niques for placing commands within the menu system. Their ultimate goal is to minimize selection time (Ahlström, 2005; Bailly et al., 2016; Card et al., 1980) while maximizing the associativity among commands (Bailly et al., 2013; Dayama et al., 2021). In order to reach these goals, the setup of parameter-based models needs to possess complete information regarding the frequency of command usage and the relation among commands (e.g., pairwise semantic relevance scores (Bailly et al., 2014; Chen et al., 2015)). The designer typically provides the parameters for menu system design. This means that designers must rely on user testing and past experience by comparing commands with each other to determine the parameters. However, as the number of commands increases, this process can become increasingly challenging, time-consuming, and prone to inaccuracy. Furthermore, designers strive to maintain consistency across menus within a given ecosystem. This involves placing commands similarly across menus to help users quickly locate the desired command. The downside is this process of ensuring consistency can be time-consuming and distract designers from their primary goal of optimizing the menu.

Prior researches have investigated using data-driven methods such as pre-trained static embeddings (Adar et al., 2014; Li et al., 2018) to capture the semantics of menu commands. However, these embeddings are typically trained on generic datasets such as Wikipedia or limited program-specific data. Consequently, these embeddings may not effectively capture the systemic or semantic relationships specific to the domain of menu systems, resulting in limited applicability. Despite the advancements in neural language models, menu design using data-driven methods has not kept pace. There are two main reasons for this: (i) the cost of providing datasets for menu design is expensive, and (ii) menu design is an interactive process that requires input, feedback, and adjustments from the

designer. Parameter-based models give designers a sense of control over the output, and their predictability allows for a clearer understanding of how different inputs will impact the final design. Therefore, parameter-based methods are more preferred over data-driven methods in menu design.

Recent advancements in pre-trained large language models (LLMs), such as GPT-3 (Brown et al., 2020) and PaLM (Chowdhery et al., 2022), have shown emergent abilities (Wei et al., 2022a) to adapt to a range of different tasks with just a few examples of the target task. The in-depth knowledge of these models presents an exciting opportunity to facilitate the menu design process without requiring training or specific datasets. The conversational nature of open-domain dialogue systems built on top of these models also can serve to fulfill the interactive demands of design.

In this work, we present MENU-CRAFT, an AI assistant that incorporates an open-domain dialogue language model to design menus. MenuCraft utilizes the effectiveness of data-driven methods while maintaining interactive design procedures. With MenuCraft, designers can easily create menus, receive suggestions from the assistant, and ask for adjustments to enhance their menu design. For an assistant to be useful in menu system design, it needs to be versatile enough to handle a variety of tasks, ranging from the simple, like adding a command to a menu tab, to complex ones, such as suggesting alternative designs, grouping commands, and applying restrictions to the menu, tabs, or individual commands. To avoid the cost of collecting data and training multiple models for different tasks, we propose using few-shot learning methods. Our tool facilitates various menu design tasks, including topic and command-based menu design, and provides recommendations for commands and hotkeys. Furthermore, our tool enables designers to easily create custom tasks, providing them with the flexibility to tailor the system to their specific needs. From an HCI viewpoint, we intend to utilize MenuCraft to study how designers engage with language models, the types of tasks they request, and the efficacy of the models in fulfilling those requests. In summary, our contributions are the following:

- (1) We present a platform for collaborative menu design between a human designer and a large language model.
- (2) We illustrate how few-shot learning can offer a range of interactive menu design experiences,

all without requiring additional model training.

The rest of the paper is organized as follows: Section 2, introduces the related works. Section 3 and 4, describes MenuCraft and what interactions it supports. Lastly, we give our final remarks and discuss our future work in Section 5.

## 2 Related Work

### 2.1 Bridging Menus and Natural Language

Menu systems can be categorized as a user interface (UI) type. In this sense, significant research in this area has been aimed at bridging graphical UIs (GUIs) with natural language. For instance, some studies have focused on predicting alt-text labels for GUI components (Li et al., 2020; Zhang et al., 2021) or generating text summaries for the entire screen (Leiva et al., 2022; Wang et al., 2021). However, these approaches may not be well-suited for menu systems due to the limitation of capturing the entire menu in a single UI screenshot. Additionally, these researches have been focused on connecting the graphical aspects of the UI to natural language, not addressing the structural characteristics of menus or their textual representations.

Despite the potential benefits of bridging menu systems and natural language, there has been limited research in this area. One possible explanation for this is the lack of comprehensive textual datasets for menu systems since most data about different menu system applications are dispersed across the internet or embedded within software applications. In an attempt to gather a dataset for menu systems, Bailly and Malacria (2013) has succeeded in building a menu-logger tool to extract the hierarchies of the menu system for Mac OS X applications. Bailly et al. (2013) provide an open dataset of 68 applications gathered with this tool to compute associativity score between the commands. Nevertheless, this data only contains limited data on menu system hierarchies for Mac OS X applications and no descriptions or information about commands. In another attempt, Adar et al. (2014) train a word2vec model to capture the domain-specific language of Photoshop application by mining a large corpus of web documents related to the application. However, the static representations derived from the trained model are limited to a specific application domain.

There is a noticeable gap in research on integrating menu systems with natural language processing.

Our work contributes to this gap by leveraging the few-shot learning capability of LLMs to apply their extensive knowledge to various menu design tasks. Our method **does not need additional datasets** or training.

## 2.2 Interactive Application of Large Language Models

Language models, especially LLMs, have the potential to be effectively used for few-shot learning. LLMs facilitate in-context few-shot learning through prompting. Rather than finetune or re-train models for each new task, a few input and output data examples from the target task can be provided as prompts to the LLM (Brown et al., 2020; Chowdhery et al., 2022; Wei et al., 2022b; Zhou et al., 2022). This advantage enables these models to not require explicit training and can support a variety of creative tasks, especially in HCI research (Morris et al., 2022), such as story writing (Chung et al., 2022; Coenen et al., 2021; Yuan et al., 2022), modifying web designs (Kim et al., 2022), conversational interactions on mobile UIs (Wang et al., 2022), email writing (Goodman et al., 2022) and executing robot commands (Ahn et al., 2022). To the best of our knowledge, no one has yet attempted to use language models for menu design. Our platform proposes using language models in dialogue, which leverage pre-existing knowledge and **interactive design process**.

## 3 The MenuCraft

MenuCraft is an interactive assistant tool designed to assist designers in creating menu designs from scratch, offering alternative designs, command and hotkey suggestions, and more. The user-friendly web interface of MenuCraft is designed as a traditional chatbot, enabling users to engage with the tool seamlessly. Additionally, MenuCraft provides a variety of default supported interactions that can be conveniently inserted into the chat feed as templates. Users can easily modify the prompts to suit their queries, allowing for a customized experience catering to individual needs.

MenuCraft’s remarkable capabilities result from using open-ended dialog systems built on large language models. The dialog system we use is ChatGPT (OpenAI, 2022), AKA GPT-3.5-turbo, a language model capable of following instructions and answering questions posed in a conversational format. ChatGPT trained using Reinforcement Learn-

ing from Human Feedback (RLHF), using the same methods as InstructGPT (Ouyang et al., 2022), but with slight differences in the data collection setup.

### 3.1 Initialize

ChatGPT is designed to take as input the previous turns in a conversation and utilize them to generate a prediction for the subsequent turn. For MenuCraft, the few-shot learning examples are formulated as a conversation between a human designer and an AI assistant. In our initial tests, we found it very convenient to construct few-shot learning contexts for the dialog model since humans are familiar with the conversational format and can quickly adapt to it.

To set the initial prompt, we determined the primary goals of MenuCraft. As previously stated, the objective of optimizing the arrangement of commands is to improve selection time and enhance the associativity among the commands. Usually, frequently used commands are prioritized to reduce selection time by placing them at the top of the menu based on Fitts’ Law (Ahlström, 2005; Bailly et al., 2013; Cockburn et al., 2007). This approach minimizes the time required for users to access commonly used commands. To maximize associativity, commands with related operations are grouped and placed within the same tab and near each other (Bailly et al., 2013). This meets the user’s expectation of finding related menu commands in familiar locations due to spatial memory (Cockburn et al., 2007). For instance, it is intuitive that users expect to see commands such as *Cut*, *Copy*, and *Paste* to be grouped or *About* and *Help* commands to be located within the last tab. With these objectives in mind, we formulated our initial prompt as follows:

---

Initial Prompt

I want you to act as an AI-Assisted Menu Designer, called MenuCraft. You will come up with design ideas for menu user interfaces that make apps easier to use. You may suggest menu design apps for a topic, arrange commands as linear or hierarchal menus, group the commands as tabs, suggest command names, add or suggest hot keys for the commands, and so on - but the aim is to design a menu that users find satisfying to use, meaning select good names for commands, prioritize frequently used commands for each tab of menu as the top, and put commands with close logical operations in the same tab. If you understand the your responsibilities, introduce yourself in short and asks for the user request.

---

MenuCraft responds with:

```
_____ MenuCraft _____  
I am MenuCraft, an AI-Assisted Menu Designer designed to help create intuitive and user-friendly menu interfaces for various types of applications. I can suggest menu design ideas, arrange commands in linear or hierarchical menus, group commands as tabs, suggest command names, and hotkeys, and more to make the app easier to use. What would you like me to help you with?
```

Now that initialization has been completed, design requests can be submitted.

## 4 Supported Interactions

In this section, we describe a number of the interactions that MenuCraft can perform.

### 4.1 Topic-Based Design

Topic-based design is one of the most general tasks that a designer can ask MenuCraft to perform. MenuCraft can assist in the creation of a menu for a specific topic by suggesting relevant commands based on similar apps and user input constraints. For example, when MenuCraft is prompted with:

```
_____ Human Designer _____  
Create a menu for a text editor application with 3 tabs. There should be a `Find` command in the `Edit` tab in the app. Tabs should not have more than 6 commands each. Please answer in the following format:  
```json  
Tab: list of commands  
```
```

MenuCraft responds with:

```
_____ MenuCraft: Topic-Based Design _____  
Certainly! Here's a menu design for a text editor application with 3 tabs, including the `Find` command in the `Edit` tab, and no more than 6 commands per tab:  
{  
  "File":  
    ["New", "Open", "Save", "Save As...", "Print", "Exit"],  
  "Edit":  
    ["Undo", "Redo", "Cut", "Copy", "Paste", "Find"],  
  "Format":  
    ["Font", "Bold", "Italic", "Underline", "Strikethrough", "Highlight"]  
}
```

This response completely fulfilled the request and met the conditions. The designer can [continue the interactions](#) for the new requests or

modifying the suggested menu. For example, designer can request the *Format* tab be deleted, and in its place the *View* tab and any commands required be added:

```
_____ Human Designer _____  
Remove the `Format` tab from the current design and replace it with a `View` tab with the commands that are needed.
```

MenuCraft responds with the same menu, replacing the *Format* Tab with *View* Tab. The replaced tab (other tabs were not shown for better readability):

```
_____ MenuCraft: Modify Design _____  
"View":  
  ["Zoom In", "Zoom Out", "Full Screen", "Show/Hide Ruler", "Show/Hide Gridlines", "Show/Hide Document Outline"]
```

The *View* tab has been successfully added with relevant commands, such as *Zoom In* and *Zoom Out*.

### 4.2 Command-Based Design

Command-based design is the primary focus within the menu design community. In this scenario, the designer provides a set of commands and their corresponding parameters, including the frequency of usage for each command and the association score between each pair of commands. Given the parameters, the designer then requests a menu optimizer to provide an optimal or sub-optimal design. As the number of commands increases, optimization methods may take hours or even days to find an optimal solution. Conversely, while language model approaches may not yield the optimal answer, they can likely provide an appropriate one within seconds. Furthermore, unlike optimization methods, language models do not require access to the entire set of parameters but welcome any input from the designer. For example, when MenuCraft prompted with random order of 5 tabs and 29 commands of Windows Notepad application, without saying these commands belong to this application:

```
_____ Human Designer _____  
Design a menu for a text editor app only based on the provided commands and tabs. Each tab should have the most frequently used commands as its top, and commands with close logical operations should be grouped together as tabs. To show some of the commands in a tab are more related, you may use some subgroups for each tab.
```

```

Commands provided (unordered):
[`\View Help`, `About Application`, `Paste`,
`Save As`, `Open`, ...]
Tabs provided (unordered):
[`\Format`, `File`, `View`, `Help`, `Edit`]
Please answer in the following format:
```json
Tab: list of commands
```

```

---

### MenuCraft responds with:

```

----- MenuCraft: Command-Based Design -----
Here's a suggested menu design for a text
editor app based on the provided commands
and tabs:
{File:
  ["New", "New Window", "Open",
  "Save", "Save As", "Page Setup", "Print",
  "Exit"],
Edit:
  ["Undo", "Cut", "Copy", "Paste",
  "Delete", {"Find": ["Find...",
  "Find Next", "Find Previous",
  "Replace..."]}, "Select All",
  "Time/Date"],
Format:
  ["Word Wrap", "Font..."],
View:
  [{"Zoom": ["Zoom In", "Zoom Out",
  "Restore Default Zoom"]}, "Status Bar"],
Help:
  ["View Help", "Search With Bing",
  "Send Feedback",
  {"About": ["About Application"]}]}

```

In this menu design, the commands are arranged in hierarchical order with frequently used commands appearing at the top of each tab. The File tab includes essential file-related actions such as creating, opening, saving, and printing files. The Edit tab includes common text-editing actions such as undo, copy, paste, and find/replace. The Format tab includes options for formatting text, including word wrap and font selection. The View tab includes commands for adjusting the zoom level and displaying the status bar. The Help tab includes options for getting help, searching for information, and providing feedback. I hope this menu design meets your needs and provides a user-friendly interface for your text editor app!

---

This design has a lot in common with the original Windows Notepad design. The commands' order and grouping are the same except for a few commands. For example, *Search With Bing* is now located under the *Help* tab, which may not be a bad idea. In the following, MenuCraft explains why it chose this particular design. The designer can always ask for the reasoning behind the design or ask the MenuCraft to **think step-by-step and explain** why it is taking each action.

### 4.3 Command or Tab Recommendation

MenuCraft can provide valuable suggestions for related commands or tabs for a particular design. This can save designers time and effort while also improving the overall user experience of the design. For example, asking MenuCraft about related commands under a tab and why these commands were chosen:

```

----- Human Designer -----
My app menu design already includes `Book-
mark this Tab` under the `Bookmarks` tab.
What other commands should I include under
this tab?
Please answer in the following format
```json
command name: reason
```

```

---

### MenuCraft responds with:

```

----- MenuCraft: Command Recommendation -----
Certainly, here are some additional com-
mands that could be included under the
"Bookmarks" tab with a brief reason for
each:
{
  "Bookmark All Tabs": "Enables users to
save bookmarks for all currently open tabs
in a single action.",
  "Organize Bookmarks": "Opens a bookmark
manager or dialog that allows users to sort,
categorize, and manage their saved book-
marks.",
  "Edit Bookmark": "Lets users modify the
properties of an existing bookmark, such as
the title, URL, or tags.",
  "Remove Bookmark": "Deletes a selected
bookmark from the user's list of saved book-
marks.",
  "Import Bookmarks": "Allows users to im-
port bookmarks from a different browser or
bookmarking service.",
  "Export Bookmarks": "Enables users to ex-
port their bookmarks to a file or other ex-
ternal location.",
  "Bookmarks Sidebar": "Toggles the display
of a sidebar or panel that shows the user's
saved bookmarks.",
  "Recently Bookmarked": "Displays a list
of recently bookmarked pages or URLs for
quick access."
}

```

---

We found the response quite good. In many cases, these commands already exist in popular browsers. They allow users to manage and organize their bookmarks more effectively.

### 4.4 Command or Tab Name Recommendation

MenuCraft can help designers generate appropriate names for commands based on their descriptions

or suggest names for tabs based on the set of commands they contain. For example, asking MenuCraft about a menu tab name based on two known commands inside it:

---

Human Designer

There is a nameless tab on my menu design that includes commands such as "Minimize" and "Zoom". Please suggest top best 10 names for this tab.

---

MenuCraft responds with:

---

MenuCraft: Tab Name Recommendation

Sure! Here are ten potential names for the tab that includes commands like "Minimize" and "Zoom":

Window, Display, View, Layout, Screen, Desktop, Workspace, Monitor, Size & Position, Display Options

These names are intended to convey the idea of adjusting the window or interface in various ways, such as changing the size, position, or arrangement of elements on the screen. Hopefully, one of these names fits well with the intended purpose of the tab and helps users easily locate the relevant commands.

---

There are several good suggestions for the desired tab name in the response. For instance, one can find both *Minimize* and *Zoom* commands in the *Window* Tab (MenuCraft's first choice) of Chrome browser on MAC OS X.

#### 4.5 Hotkey Recommendation

Hotkeys, also known as keyboard shortcuts, are a combination of keys on a computer keyboard that provide a quick way to access various menu commands. The selection of well-thought-out hotkeys can speed up access to frequently used commands. MenuCraft simplifies this process by creating hotkeys based on menu design, reducing the time and effort required. Hotkeys must be distinct from other commands in the app. For example, continuing the first design of the text editor in section 4.1, by requesting to add shortcuts:

---

Human Designer

Add shortcut for each command, two different commands must not have the same shortcut.

---

MenuCraft responds with:

---

MenuCraft: Hotkey Recommendation

Certainly! Here's the updated menu design for a text editor application with 3 tabs, including the Find command in the Edit tab, no more than 6 commands per tab, and keyboard shortcuts for each command:

```
{ "File": [
  { "name": "New", "shortcut": "Ctrl+N"},
  { "name": "Open", "shortcut": "Ctrl+O"},
  { "name": "Save", "shortcut": "Ctrl+S"},
  { "name": "Save As...",
    "shortcut": "Ctrl+Shift+S"},
  { "name": "Print", "shortcut": "Ctrl+P"},
  { "name": "Exit", "shortcut": "Alt+F4"}
],
"Edit": [
  { "name": "Undo", "shortcut": "Ctrl+Z"},
  { "name": "Redo", "shortcut": "Ctrl+Y"},
  { "name": "Cut", "shortcut": "Ctrl+X"},
  { "name": "Copy", "shortcut": "Ctrl+C"},
  { "name": "Paste", "shortcut": "Ctrl+V"},
  { "name": "Find", "shortcut": "Ctrl+F"}
],
"Format": [
  { "name": "Font",
    "shortcut": "Ctrl+Shift+F"},
  { "name": "Bold", "shortcut": "Ctrl+B"},
  { "name": "Italic", "shortcut": "Ctrl+I"},
  { "name": "Underline",
    "shortcut": "Ctrl+U"},
  { "name": "Strikethrough",
    "shortcut": "Ctrl+Shift+S"},
  { "name": "Highlight",
    "shortcut": "Ctrl+H"}
]
}
```

I've added keyboard shortcuts for each command to make it quicker and easier for users to access frequently used commands. The shortcuts are listed next to each command in the format of Ctrl+Key or Ctrl+Shift+Key.

---

Most of the selected shortcuts are commonly used by other applications, such as *Ctrl + Z* for the *Undo* command. The rest is made up of the *Ctrl* key and the first letter of the command. To prevent shortcut reuse, the *Ctrl + Shift* combination is used. Nevertheless, an error occurred when assigning the shortcut for the third time to a command that starts with the letter S (*Strikethrough*). MenuCraft can be instructed about what other templates it can use to create shortcuts to prevent this from happening. However, the designer can also inform MenuCraft of its mistake through [more interaction](#):

---

Human Designer

The same shortcut must not be shared by two commands, even in different tabs. `Strikethrough` and `Save As...` share a same shortcut.

---

MenuCraft replies with a *thank you for clarifying* and corrects its mistake by replacing the shortcut for *Strikethrough* command (other tabs were not shown for better readability):

———— MenuCraft: Hotkey Modification ————

Thank you for the clarification Here's an updated menu design ensuring that no two commands share the same shortcut even in different tabs:

```
...
{"name": "Strikethrough",
 "shortcut": "Ctrl+Shift+D"},
...
```

I changed the shortcut for Strikethrough to Ctrl+Shift+D to ensure that it does not share the same shortcut as Save As.... This will help users avoid confusion and make it faster to perform specific tasks with the text editor.

In the revised response, it was suggested to use another shortcut (*Ctrl+Shift+D*) for the *Strikethrough* command. This suggestion is acceptable since popular applications such as Microsoft Excel also use the same shortcut.

#### 4.6 Command Elaboration

MenuCraft can provide additional information about specific commands in a menu. It can explain the meaning of a command or provide examples of how it could be used in context. This feature can assist in verifying whether an intelligence understands the functionality of a command based on its name in a given context. Additionally, it can generate documentation for the designed menu. For example, continuing the first design of the text editor in section 4.1 by requesting an elaboration on designed menu commands:

———— Human Designer ————

Provide a short elaboration on the designed menu commands for the text editor. The format should be as follows:

```
...
tab name, command: short elaboration
...
```

MenuCraft responds with:

———— MenuCraft: Command Elaboration ————

File Tab:

- New File: creates a new blank document
- Open File: opens an existing file for editing
- Save: saves the current document
- Save As: allows the user to save the document under a different name or file type
- Print: prints the current document
- Exit: closes the application

Edit Tab:

- Undo: reverses the last action performed
- Cut: removes the selected text and copies it to the clipboard
- Copy: copies the selected text to the clipboard
- Paste: inserts the contents of the clipboard at the current cursor position
- Find: searches for a specific word or phrase in the document
- Replace: allows the user to replace a specific word or phrase with another

Format Tab:

- Font: allows the user to change the font, size, and style of the selected text
- Bold: makes the selected text bold
- Italic: makes the selected text italicized
- Underline: adds an underline to the selected text
- Strikethrough: adds a strikethrough to the selected text
- Highlight: highlights the selected text with a color

Each command has been explained in a fair and reasonable manner.

## 5 Conclusion and Future Work

MenuCraft represents a promising new direction in menu design through language models. Our initial experiments have shown that MenuCraft can perform various menu design tasks quite well. However, MenuCraft is still in the prototype phase and needs much more to explore. Moving forward, our future work with MenuCraft will focus on conducting additional user studies to gain further insights into the needs and preferences of menu designers. This will allow us to tailor MenuCraft to meet the specific requirements of different users and contexts. Furthermore, we will explore how the data collected from MenuCraft and designer feedback can be leveraged for better prompt engineering. Overall, we are excited about the potential of MenuCraft and look forward to continuing our work in this area. This new direction has the potential to revolutionize menu design and improve the user experience across a wide range of applications.

**Discussion.** There is a discussion in the design community about rethinking the way AI supports designers (De Peuter et al., 2021). Their view is that AI should prioritize cooperation over automation and seek to enhance the creativity and problem-solving abilities of designers. The challenge is that design is an optimization problem, but integrating a human decision-maker into an optimization

process is hard due to the differences in the way humans and optimizers think and work. Our view is that MenuCraft has already close to achieving this objective for two reasons:

- (1) As ChatGPT is trained on a large corpus of data, and human feedback is also used in the training, we expect ChatGPT to develop a good understanding of the behavior of human designers.
- (2) Humans are intuitively familiar with conversational formats, and ChatGPT is capable of following instructions posed in a conversational format.

**Limitations.** Language models offer a promising new direction for menu design, but it is essential to acknowledge their limitations. Language models may lack domain-specific knowledge for menu design, and their performance is heavily influenced by the quality and diversity of the training data used. Moreover, Language models may struggle with understanding mathematical concepts, particularly when designers input specific parameters for design features. This limitation could result in poor design recommendations. Furthermore, MenuCraft has demonstrated acceptable results with ChatGPT, but extending these results to other LLMs is currently limited by the lack of experiments with multiple models.

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## A Prototype Demonstration

Here is a simple example of a designer interacting with the prototype version of MenuCraft: <https://kargaranamir.github.io/MenuCraft/>