

ChoiceMates: Supporting Unfamiliar Online Decision-Making with Multi-Agent Conversational Interactions

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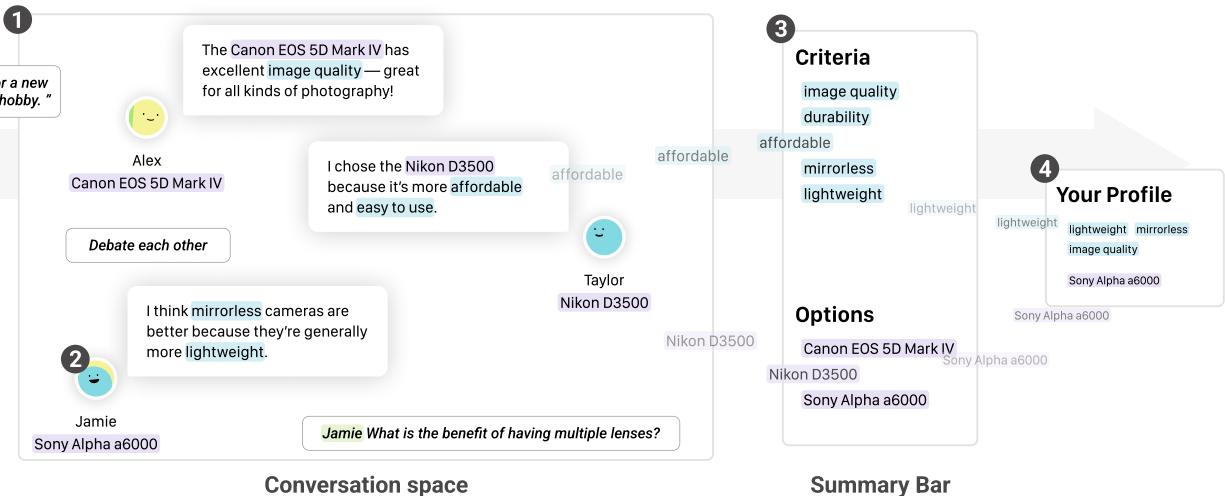


Figure 1: ChoiceMates is a multi-agent conversational system designed to support online decision-making in unfamiliar domains. In ChoiceMates, the user can converse with any selected set of agents (2) in the conversation space (1) to gather sufficient information about the domain, and use the criteria and options in the summary bar (3) to manage the information found and pin important keywords to the profile card (4) to build preference and make a decision.

ABSTRACT

Unfamiliar decisions—decisions where people lack adequate domain knowledge or expertise—specifically increase the complexity and uncertainty of the process of searching for, understanding, and making decisions with online information. Through our formative study ($n=14$), we observed users' challenges in accessing diverse perspectives, identifying relevant information, and deciding the right moment to make the final decision. We present ChoiceMates, a system that enables conversations with a dynamic set of LLM-powered agents for a holistic domain understanding and efficient discovery and management of information to make decisions.

Agents, as opinionated personas, flexibly join the conversation, not only providing responses but also conversing among themselves to elicit each agent's preferences. Our between-subjects study ($n=36$) comparing ChoiceMates to conventional web search and single-agent showed that ChoiceMates was more helpful in discovering, diving deeper, and managing information compared to Web with higher confidence. We also describe how participants utilized multi-agent conversations in their decision-making process.

CCS CONCEPTS

- Human-centered computing → Interactive systems and tools; Natural language interfaces.

KEYWORDS

Multi-Agent Interaction, Conversational User Interface, Large Language Models, Decision-Making Support, Human-AI Interaction

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arXiv, October, 2023,

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ACM ISBN XXX-X-XXXX-XXXX-X/XX/XX.
<https://doi.org/XXXXXXXX.XXXXXXX>

ACM Reference Format:

Jeongeon Park, Bryan Min, Xiaojuan Ma, and Juho Kim. 2023. ChoiceMates: Supporting Unfamiliar Online Decision-Making with Multi-Agent Conversational Interactions. In *arXiv October, 2023*. ACM, New York, NY, USA, 24 pages. <https://doi.org/XXXXXXXX.XXXXXXX>

1 INTRODUCTION

People make online decisions every day, from purchasing a new product, choosing a trip destination, to taking on a new hobby. In making a decision, people inherently go through a set of steps including recognizing the need, collecting information, identifying and ranking criteria, identifying and evaluating alternatives, and deciding an alternative [54]. However, making an *unfamiliar* decision—a decision-making situation where an individual lacks knowledge and preference in the domain—requires individuals to first grasp the fundamental knowledge of the domain before delving into the decision-making process [5, 33]. Such lack of familiarity makes decision-making more difficult as it requires the user to continually switch between learning about the domain and evaluating options [6, 57, 58].

While prior work has demonstrated effective support for online decision-making, these works have focused on providing support for managing and organizing important criteria and alternatives in the domain rather than uncovering and understanding them [9, 48, 49]. This lack of support can increase information overload for unfamiliar decision-making situations [27, 64]. As a result, this can lead to a significant investment of time and cognitive resources in grasping domain details and eliciting preference, potentially causing individuals to make uninformed decisions or even give up on making the decision entirely [29, 69].

Recommender systems aim to simplify decision-making by suggesting personalized options [10, 24]. Yet, for novices in a domain, these preferences might not be well-elicited [52, 63]. This can cause an over-reliance on the system, especially if the novices cannot detect errors due to their limited knowledge [59]. Ultimately, it almost appears that to make well-informed online decisions, novices *must* conduct thorough research of the unfamiliar domain individually.

We see an opportunity in large language models (LLMs) to better assist the workflow of unfamiliar decision-making. Their demonstrated effectiveness as informative conversational systems [39] shows promise for supporting domain novices in understanding an unfamiliar domain landscape while attaining recommendations with rich context. In this work, we focus on the unique challenges and needs of *unfamiliar* decision-making and aim to equip users with an LLM-powered interface to navigate the decision-making process in an unfamiliar domain.

To understand how people make unfamiliar decisions with online information, we conducted a formative study with 14 participants who had experience making decisions online. From observing and interviewing about their decision-making process in unfamiliar domains, we discovered that participants struggled to (1) find diverse perspectives in the domain, (2) identify relevant information among an overwhelming amount, and (3) indicate a confident end to the process.

Our formative study revealed that existing methods struggled to offer diverse and relevant viewpoints, which inspired us to bring in multiple agents powered by LLM to assist the decision-making

process. We developed **ChoiceMates**, a multi-agent conversational system that supports unfamiliar decision-making with a group of LLM agents. In ChoiceMates, the user can converse with any individual or group of *agents* (Fig.1-2) characterized by unique personas in the domain through the *conversation space* (Fig.1-1). Auto-detected criteria and options from the conversation appear in the *summary bar* (Fig.1-3) to help the user uncover and keep track of the key information found, and the user can save criteria and options on the *profile card* (Fig.1-4) to shape their preferences and make a final decision.

We conducted a between-subjects user study to evaluate whether ChoiceMates could effectively support unfamiliar decision-making. Comparing ChoiceMates with a web search condition and a prompt-tuned ChatGPT condition, the study revealed that ChoiceMates successfully supported users in exploring, diving deeper, and flexibly managing diverse information in the domain in comparison to Web with higher confidence. ChoiceMates performed similarly to SingleAgent, but there were benefits of ChoiceMates to SingleAgent in terms of eliciting multiple perspectives and gaining more control over the process which we discuss in the discussion section. In addition, we report on representative patterns of how users utilized ChoiceMates for decision-making.

This research makes the following contributions:

- A formative study uncovering the challenges and needs of unfamiliar decision-making.
- ChoiceMates, a multi-agent conversational system designed to support unfamiliar decision-making through conversation modes and a summary bar.
- A user evaluation of ChoiceMates demonstrating that users were able to go through more diverse and comprehensive information and flexibly manage the information found in the decision-making process compared to Web with more confidence.

2 RELATED WORK

Our work addresses the challenges in online unfamiliar decision-making by leveraging the benefits of multi-agent conversations powered by LLMs. We review prior work on online decision-making support, conversational interfaces for online decision-making, and designs of multi-agent systems.

2.1 Online Decision-Making Support

Due to the enormous amount of information online, online decision-makers can face information overload [70], which negatively influences the resulting decision quality [38, 60]. For unfamiliar decisions where users do not have sufficient knowledge or expertise in the domain, searching for information becomes particularly challenging [5, 33].

One thread of research focused on identifying selection criteria among a wide range of options to choose from. Mesh proposed consumer product decision-making through comparison tables and customizable preference settings [9], and Unakite and Crystalline supported software developers' decision-making with web content snippets and comparison tables [48, 49]. While these systems provide strong support for utilizing necessary information to make decisions, they do not sufficiently support information searching

and understanding for users without knowledge in the domain [27, 64].

Meanwhile, recommender systems can guide users unfamiliar with the domain by providing personalized options for users to choose from [10, 24, 65]. However, one-shot recommender systems are insufficient to support users in learning about the domain for unfamiliar decisions as the interaction is uni-directional [30]. This can decelerate users from forming their preferences during the decision-making process [52, 63, 73]. Conversational recommender systems (CRS) build on top of existing recommender systems by offering the ability to make back-and-forth exchanges of messages to continually provide contextualized and relevant recommendations throughout the user’s learning and decision-making process [30, 72, 74]. In CRS, the user can communicate through natural language interactions to solicit exact user preferences [20].

ChoiceMates is primarily inspired by the benefits of CRS in providing personalized recommendations and guidance for preference elicitation and aims to expand that to unfamiliar decision-making situations where a holistic understanding of a domain is crucial for making a confident decision. We additionally incorporate the benefits of web-based decision-making support systems to identify and manage key criteria and options in the domain better.

2.2 Text-Based Conversational Interfaces for Information Seeking

Text-based conversational user interfaces (CUIs) have been utilized for many tasks due to their ability to provide information in a digestible, human-like manner and facilitate adaptive exploration of information [18, 45, 76, 77].

In utilizing its benefit, Searchbuddies explored embedded search engine agents in social media message threads to provide easy access to relevant information online [25]. Gupta et al. showed that providing online housing recommendations through conversational interfaces built user trust and satisfaction more effectively than non-conversational interfaces [22]. Prior work has also proposed a viable framework defining that conversational interfaces can be integrated with information search to provide a more effective process for personalized recommendations and multi-turn interactions across a set of search items [61].

The recent surge of large language models (LLMs) has revealed the potential for more capable CUIs across diverse domains ranging from programming to searching for UI [46, 56, 71]. Their ability to synthesize and generate text makes them resourceful in many domains available to the public, and their ability to dynamically provide responses to user prompts makes for more adaptive and engaging conversational agents with less engineering effort. Thus, existing work and products have utilized the potential of LLMs in supporting information exploration for learning and decision-making [2, 3, 19]. For example, ChatGPT Plugins are designed to support real-world tasks such as trip planning, giving the users access to more personal and specific information [2].

While conversational interfaces adaptively provide information through a multi-turn process, conversing requires the user to articulate their input clearly which, if not done, could result in misinterpreted user intent and irrelevant responses [7, 17, 28, 53, 79]. To complement that, existing work has demonstrated techniques to

bring multi-modal inputs such as a graphical user interface (GUI) to repair conversational breakdowns [43, 44]. Moreover, Sensecape demonstrated support for nonlinear, multi-level exploration and sensemaking of LLM-generated text to empower users in the sensemaking process [67].

ChoiceMates builds on these LLM-powered conversational interfaces by providing interactive and digestible conversations to support online decision-making. In addition, ChoiceMates adds on direct manipulation of objects as an interaction modality on top of natural language, where actions such as pinning valuable criteria or options are fed into the conversation as a context.

2.3 Multi-Agent Interfaces

Previous works presented systems that introduced the interaction between multiple agents that simulate human conversation, cooperate to solve tasks, and process user inputs.

A number of existing work has demonstrated the simulation of multi-person communication with LLM-powered agents, showing these personas closely resemble communications between real users by displaying different personas [11, 14].

Multi-agent systems have also been used to solve complex tasks, by utilizing agents for microtasks or having them collaborate or debate to elicit a wide range of information and opinions. One popular approach is self-prompting, an architecture for feeding LLM-generated responses into other LLMs to complete information tasks autonomously [1, 16, 26, 41]. Other frameworks have also been presented for building multi-agent autonomous LLM architectures [68]. In addition, AutoGen provides a framework for supporting flexible multi-agent conversation patterns, which can be employed across various applications, including online decision-making [75].

Another line of work investigates how the user manages and converses with multiple agents to get support on complex tasks. Many human tasks benefit from collaboration and information integration from various sources [15, 21] compared to the individual cognitive processes in isolation. These systems capitalize on their abilities to delegate tasks to multiple agents, communicate and collaborate among the agents, and provide unique identities [34, 35, 42]. Zolitschka et al. proposes a unique approach to automatically orchestrate and coordinate multiple agents for a given user input message [78], and ChatEval utilizes a multi-agent LLM system for evaluating text using responses from multi-agent debates [8]. CommunityBots utilizes a set of agents handling a unique domain each, supporting topic- and chatbot-switching based on user interactions [32].

In ChoiceMates, we leverage the advantage of having multiple agents to support the decision-making process, where the agents reveal similar and opposing viewpoints toward the user’s utterance or inquiry. In addition, instead of automatic orchestration among agents to provide agent response, we provide authority to the user, so that the user can choose a set of agents they relate the most to converse with for a better understanding of the available perspectives to make a more informed decision.

3 FORMATIVE STUDY

To design an approach to support unfamiliar decision-making, we first aimed to understand the common practices in unfamiliar decision-making and uncover the challenges in the process. For this purpose, we conducted semi-structured interviews with 16 participants with prior experience in unfamiliar decision-making.

3.1 Participants and Study Procedure

We recruited 14 participants (Age=18-55, M=28.2, Std=7.8; 8 males and 6 females) who had frequent experience making decisions online (details in Table 1). The recruitment took place through our university's community channels and snowball sampling to recruit participants in a wide age group. To ensure their experience in making decisions in unfamiliar scenarios, we asked the participants to list out previous experience in both familiar and unfamiliar decisions in the recruitment form.

The interview lasted for 75 minutes for each participant. First, a 20-minute semi-structured interview was conducted to understand participants' previous experiences with unfamiliar decision-making. We asked questions about the overall process, which information they utilized, and the challenges they faced in the process. Then, a 30-minute think-aloud study was conducted where participants chose an unfamiliar scenario among the given set (see Appendix A) and browsed through the internet until they identified several possible options. Lastly, participants were interviewed for 15 minutes on their experience with their process and the challenges they faced in this scenario, then on the general challenges and desired support of unfamiliar decision-making.

3.2 Findings

Here, we describe the different approaches people follow for unfamiliar decision-making and describe three main challenges we identified from the process.

3.2.1 Practice. The participants used several sources in various orders and frequencies in collecting information and making unfamiliar decisions. Each participant had a different strategy they took for the process, which involved various sources including summary posts of the domain ($n=8$), posts with individual opinions and experience ($n=10$), and websites with a list of options in the domain ($n=11$). During the interview, many ($n=12$) brought up asking an expert as their previous experience making unfamiliar decisions.

With *summarized post* such as YouTube recommendation videos or rating sites (e.g., <https://www.rtings.com/>), participants were able to objectify multiple criteria and understand the overview of the domain, but could not receive contextualized information. Participants found *posts with individual opinions*—online communities, product reviews, or blog review posts—helpful for gathering diverse opinions on the options but also mentioned that it is time-consuming to find credible sources and hinders them from utilizing individual opinions. *Browsing through a list of options* from shopping sites was another approach participants took, but they were unable to understand and compare different options without knowledge of the domain, thus switching to the other two sources of information. During the interview, 12 out of 14 participants mentioned *asking an expert*—including store managers, friends, and family who have

expertise in the decision domain—an approach they took for unfamiliar decisions as a way to receive information without being overwhelmed. They mentioned that experts' ability to (1) explain ground-based information about the domain and provide information that's difficult to find, and (2) ask clarification questions to make better suggestions in one's specific context makes them reach out to experts for unfamiliar decisions.

3.2.2 Challenges. We identified three main challenges participants faced during the unfamiliar decision-making process.

C1: Difficult to find diverse perspectives. The participants found it challenging to find information that contained diverse viewpoints even through multiple sources. Some struggled to find diverse opinions about the domain: P14 (interior light) discovered new criteria as they looked at the reviews of each option, but still struggled from a lack of sufficient information. Others wanted to see information from a fresh viewpoint, to understand the information landscape of the domain. They mentioned that they wanted to see if the different perspectives they found in sum represented comprehensive information of the domain to make a more confident decision.

C2: Difficult to identify relevant information among an overwhelming amount. After they were able to find information about the domain through multiple sources, the participants faced difficulty in understanding and connecting the information to their unique situation. P4 (car seat) discovered two types of car seats and the characteristics of each but did not understand what would be better for a newborn, commented later that "I end up spending a lot of time and effort finding a good resource [that fits my context]." Most participants were successful in getting to different websites, but the ones they utilized were of a small portion in comparison to the information they accessed as they did not see others as relevant. For example, P5 (robot vacuum cleaner) found lots of recommendations online, but failed to utilize them as they were "all personal and subjective experiences, different from my situation."

C3: Don't know when and where to end. Since participants did not have intuitions on the domain due to their lack of knowledge and experience, they found it difficult to identify whether the information they had accurately described the general information of the domain. The participants constantly questioned themselves on whether there were any criteria they might have missed, which could influence the experience after the decision. Even after they identified a strong candidate, they lacked confidence and double-checked through multiple other sources whether the candidate was a suitable choice. During cross-checking, there have been cases where the participants had to reset their decisions and go for a new option. P1 (cafe catering) had to go back to the initial stage after seeing all the cafes she found lacked catering experiences. In addition, P8 (robot vacuum cleaner) described the decision scenario as a "seemingly endless amount of information" which led to additional difficulty in making a decision.

4 DESIGN GOALS

With the identified challenges in the unfamiliar decision-making process, we propose the following design goals for a system that can support unfamiliar decision-making.

ID	Age	Gender	Previous Unfamiliar Scenario	Selected Scenario
P1	26-35	F	Choosing a course to take for a summer school, Buying an oven for a baking hobby	Choosing a cafe to cater some snack food on an end-of-semester event
P2	36-45	M	Choosing a trip destination, Choosing a t-shirt for summer	Planning a solo trip destination for three days
P3	26-35	M	Buying a tennis racket, Choosing a U.S. stock option to buy	Buying a car seat for a friend's newborn
P4	26-35	F	Choosing a working holiday location, Buying a laser hair removal	Buying a car seat for a cousin's newborn
P5	18-25	M	Buying a lunch box	Buying a robot vacuum cleaner to replace the normal vacuum cleaner
P6	26-35	F	Buying a new tennis racket, Choosing meal to cook	Renting a house short-term for an internship
P7	18-25	M	Choosing a transportation card plan in a new country	Choosing a new hobby to do in free-time
P8	18-25	F	Planning a trip to Osaka, Choosing a wrist/ankle brace+lumbar support	Buying a robot vacuum cleaner to replace the normal vacuum cleaner
P9	18-25	M	Choosing a hair salon, Buying a gift for a friend	Buying a car seat for a friend's newborn
P10	18-25	M	Whether to get a CT+MRI during ER visit, Buying clothes at a flee market	Buying a skateboard for transportation purposes instead of walking to school
P11	26-35	F	Buying a coffee pod machine, Searching for a job	Buying a skateboard for transportation purposes instead of walking to school
P12	26-35	M	Buying a used phone, Planning a trip to Jeju	Buying an interior light at home
P13	18-25	M	Choosing an affordable phone plan, Choosing field of work	Buying a skateboard for transportation purposes instead of walking to school
P14	46-55	F	Choosing exercise, Buying a blue light blocking film	Buying an interior light at home

Table 1: Participant demographic for the formative study.

DG1. Support discovering of diverse perspectives in the domain. To support users in finding and understanding diverse perspectives in the domain, a wide range of values that sufficiently cover existing values in the decision domain should be provided. Furthermore, the system should support users to easily browse those values and compare them to aid an understanding of how they differ.

DG2. Provide information adaptive to user’s preferences. Among the provided information in the domain, users should be able to find the ones that are the most relevant to their context. Previous research has shown that choice-based preference elicitation is more effective for novices [51]. To support unfamiliar decisions, the system should provide users with the possible choices in the domain along with additional information to support the induction of preferences that adhere to personal context.

DG3. Enable flexible management of discovered information. The participants described the information as ‘overwhelming’ in indicating the most relevant information, comparing different opinions, and understanding the information. Since unfamiliar decision involves a wide range of information, the system should support users with user-guided filtering, clustering, and grouping at various level

(e.g., criteria, options) for flexible management of the information found throughout the process.

DG4. Support reduction of discovered criteria, preferences, and options. After finding and identifying relevant information in the domain, users should be able to converge into a set of criteria and an option to come to a conclusion. The system should help users record emerging preferences—criteria and options—throughout the process and utilize the recorded preferences in indicating a confident end to the decision.

5 CHOICEMATES: A MULTI-AGENT CONVERSATIONAL SYSTEM

From our findings and design goals, we propose a system that supports unfamiliar decision-making with **multi-agent, conversational interactions** powered by LLMs. We decided to use conversational interaction for its ability to provide information in a digestible manner and facilitate interactive exploration of information [45], and multiple agents to support the exploration of diverse viewpoints to discover personalized information [62]. We use LLMs to generate the agents for their ability to provide resourceful information in the domain [71].

We designed and developed **ChoiceMates**, a multi-agent conversational system that assists users in gaining a broad understanding of an unfamiliar domain by (1) conversing with a dynamic set of agents and (2) constructing preferences toward a decision by managing the conversation through agents. Throughout the section, we describe an envisioned user scenario, explain different components of the system, and describe the system implementation and prompt engineering.

5.1 Envisioned Scenario

Sally has recently found an interest in photography and wants to find a camera right for her. However, she is unfamiliar with the camera domain and does not know which camera she would like most. As she has no experts to consult and gets overwhelmed by the information online, Sally enters ChoiceMates and types into the message input box, “I’m new to photography, and I want a camera. Not sure which one would be best for me.” She then encounters four agents (Alex, Jamie, Taylor) appearing on ChoiceMates, each with a unique persona containing an option (i.e., a camera model) they had chosen and the criteria (e.g., portability, brand) that led to their choice. In each agent’s response, she sees the auto-detected and highlighted criteria and options.

- Alex: “As a professional photographer, I value image quality and durability in a camera. That’s why I chose the Canon EOS 5D Mark IV. It’s a full-frame DSLR that delivers excellent image quality and is built to last.”
- Jamie: “I’m a hobbyist photographer and I prefer a camera that’s lightweight and easy to use. I’ve been using the Sony Alpha a6000 and it’s been great for me. It’s compact, takes great photos, and is very user-friendly.”
- Taylor: “I’m a travel blogger and for me, portability and battery life are key. I use the Fujifilm X-T3. It’s compact, has a long battery life, and takes amazing photos. What are your needs and preferences when it comes to photography?”

Sally learns about the wide range of values and criteria different professions and lifestyles have for cameras through the agents and their profiles (**DG1**). Sally considers Jamie to be the most relatable as she is getting a camera for a hobby. Sally tags Jamie and asks why they value lightweight and easy-to-use cameras. Jamie responds that they “don’t need all the bells and whistles of a professional camera” and they “want to focus on capturing the moment”. Sally learns that for her personal use, she may want to follow Jamie’s reasoning as Sally is also looking for a simple camera. She then asks follow-up questions to Jamie on “What is considered a lightweight camera?” and “What is the main difference between a professional camera and an easy-to-use camera?” to better understand what each criterion means.

After gaining some information, she decides to get an easy-to-use camera and saves the criterion to her profile. To explore more candidates, she asks a question that reflects her preference: “Are there other easy-to-use cameras?” Three more agents with the criterion easy to use included in their valued criteria appear: Riley, Morgan, and Casey (**DG2**). Continuing the conversations with different

agents, Sally realizes that the conversation space is becoming cluttered with many agents, and decides to filter out irrelevant agents by selecting the criterion easy to use from the *Summary Bar* (**DG3**).

As Sally continues to converse and learn more, she becomes more and more confident about the set of criteria she personally values for her activities and saves those to her profile. Now that she has a clearer picture of the domain, she also wants to compare the three cameras she is currently considering in depth. She selects agents advocating for the three cameras and opens the focus view to view their detailed reasoning for their choices and how it is related to Sally’s valued criteria. By asking the agents to *debate each other*, Sally finds the Nikon Coolpix B500 best fits her preferences and pins it to her profile. She is content that she could identify the important criteria and options by constructing her profile (**DG4**). When she clicks “Done”, she reviews her criteria and what she had valued throughout her decision-making process.

5.2 System Components

ChoiceMates (Fig. 2) is an interface that allows the user to interact with a set of agents to make an unfamiliar decision. Agents are the main unit of conversation in ChoiceMates and are the basis of gaining information about the domain. This allows users to freely explore domain information while flexibly building and managing their knowledge structure.

ChoiceMates consists of a *message input box*, a *conversation space of organizational agents*, a *summary bar* consisting of criteria and options found through the conversation, and a *profile card* for saving important criteria and options that user found throughout the session. The user can 1) explore sufficient and relevant information in the domain by conversing and interacting with the agents and 2) gather relevant criteria and options and compare them to get to a decision. In this section, we first describe agents, the conversation space with the agents as well as additional support in the conversation space to manage the information, and then the summary bar and the profile card.

5.2.1 Agents. Each agent is characterized by its persona (i.e., a single-line description of the agent), a set of criteria (i.e., factors to consider in the domain) they value, and a single option (i.e., an available choice in the domain) they chose with the criteria. They are designed to reflect an individual’s choice and their underlying values and experience in real life and as a support to gaining an easy understanding of the domain and elicitation of user’s preferences by externalizing the link between an option and criteria. The constraint of one agent favoring one option was inspired by previous work showing that novices preferred case-based preference elicitation [36]. To provide a better salience of criteria and options in the domain, all criteria mentioned by agents are highlighted in blue and all options are highlighted in purple.

When the user asks an initial question in the domain, ChoiceMates prompts the LLM to generate diverse agents. Newly spawned agents always begin with an introduction of themselves, sharing their valued criteria and a chosen option. To ensure that the agents communicate with the correct information, we scrape information through Google search for facts about the agent’s option. We run the web scraping function *right after* the agent is generated to let

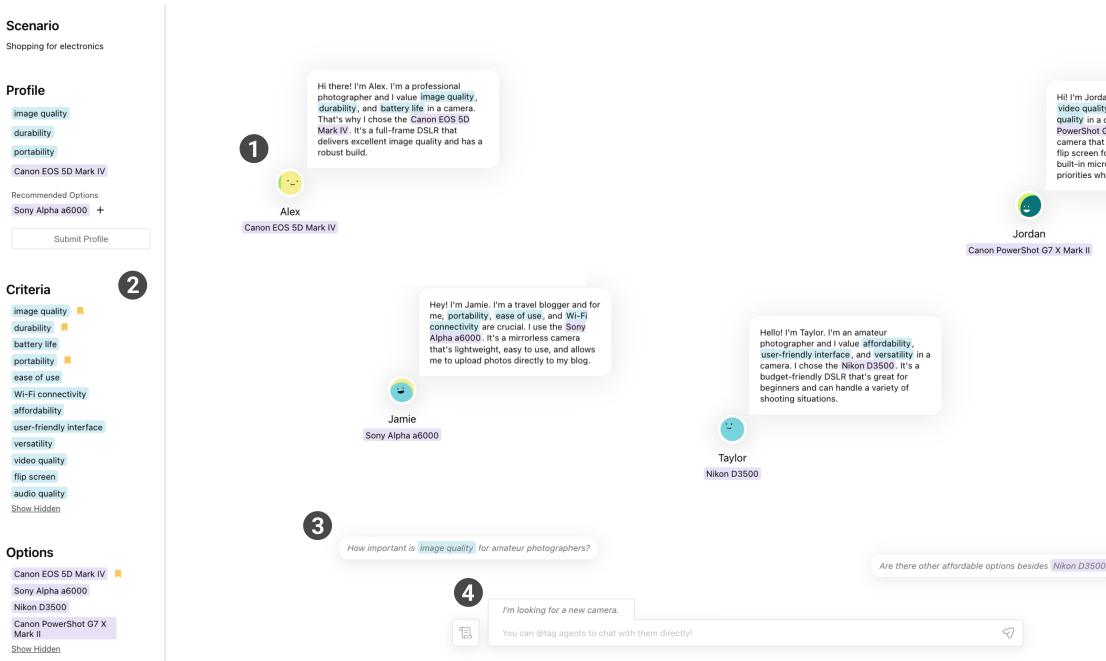


Figure 2: The ChoiceMates interface: Agents populate the conversation space to converse with the user, identifying key criteria and options in their utterances (1). The *Summary Bar* lists those criteria and options (2), additionally showing the user profile. *Thought Bubbles* recommend the user questions to ask (3), and the interface provides the user with a message input box to converse with all agents (4).

the LLM produce diverse agents without being restricted by the web-searched information. The scraped information is then provided to the agents and stays in the conversation stream with a prompt asking agents to utilize the information. This content is meant to stay in the conversation as context. Agents are by default represented by their unique icons, names, and options (Fig. 3).

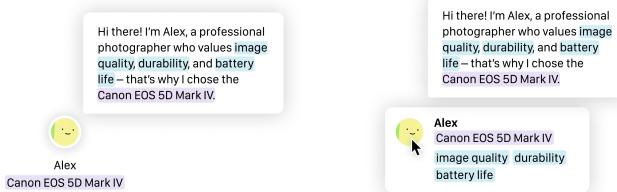


Figure 3: (1) An agent utterance is represented as a chat bubble above the agent icon. (2) Hovering over the icon reveals the agent's profile containing their valued criteria and their chosen option.

5.2.2 Conversation Space. To support the exploration of an unfamiliar domain, ChoiceMates provides a conversational space where all agents reside, allowing users to converse with and freely organize them in order to understand the overall landscape of options from agents.

Agent Conversation (Fig. 4, DG1). The formative study revealed that searching for many directly relevant perspectives is difficult in an online web search environment. Users have to sift through many sites to find such relevant experiences, and this slows down their decision-making process. On ChoiceMates, agents are designed to chat back and forth with the user (DG2). This way, users can ask follow-up questions to agents they relate to and gain a deeper understanding of domain options.

The user initiates the conversation by sharing their decision-making scenario, and three to six agents with varying persona appear on the screen. Agents then share their experiences and ask questions about the user's preferences. The user can then respond to agents through their message input box to either reply to a question or ask one themselves.

ChoiceMates provides both user-guided and system-guided selection of agents to respond. Upon receiving the user's message, ChoiceMates detects the user's intent and makes existing agents, new agents, or a combination of both to respond, depending on the agents' relevancy to the user's message and context (More described in Fig. 9) If the user wants to manually direct their response to particular agents, they can also select agents on the space (Fig. 5). Additionally, agents can converse with one another by responding to other agents in the conversation. They can agree, disagree, or ask further questions to other agents. This can reveal comparisons between options and new criteria that the user may not have thought of when they are the only ones conversing with them. Just as the user can manually select agents to respond, the user can also

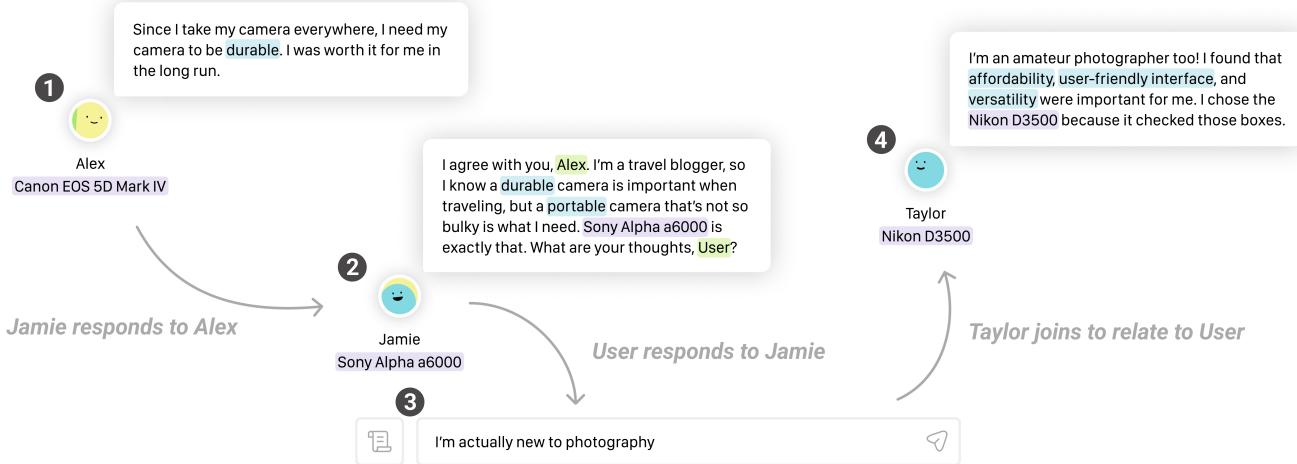


Figure 4: ChoiceMates’ multi-agent conversation is designed to provide continuous, yet controllable streams of agent conversations, inviting the user to share their personal preferences. When Alex mentions the importance of durability (1), Jamie follows up to share their experience with their chosen camera (2). Jamie brings the user into the conversation. The user then shares a different background from those of Alex and Jamie (3). This invites Taylor, an agent with a similar background to the user, to share a more relatable experience when choosing a camera (4).

manually trigger inter-agent conversations by selecting agents and asking them to “debate each other”.

Agent Management (Fig. 5, DG3). After several turns of conversation between the user and agents, numerous agents can be introduced, potentially cluttering the space. The user can select and drag agents around the space to better organize their space to manage the clutter of agents and rearrange them.

Conversation Guidance and Management (Fig. 2.3, DG2). To support users not knowing what to search for due to their lack of knowledge in the domain, ChoiceMates provides *Thought Bubbles* to provide suggestions on what to ask agents to continue their search (Fig. 2.3), inspired by the effectiveness of such guidance in prior work [67]. Thought Bubbles appear throughout the conversation and suggest utterances that guide the user to explore other criteria and options that might be relevant to them or important in the domain. The user can click on the Thought Bubbles to send the message as the user and is updated with the conversation history after each turn.

To reduce clutter from more agents and messages, we chose to only display the latest messages sent from the previous turn. Instead, users could click the button left of the message input box in Fig. 4.2 to view the conversation history.

5.2.3 Preference Construction with Summary Bar. ChoiceMates provides three representations to facilitate this stage: (1) *Summary Bar*, (2) *Focus View*, and (3) *Profile Card*.

Summary Bar (Fig. 6, DG4). To help users make sense of the information found with multiple turns, we provide *Summary Bar* that distills information into key aspects for the user to gain a broad understanding of the conversation and the domain. Criteria and options are detected and highlighted as agent messages are

generated and are listed in the *Summary Bar*. The user can hover over criteria and options to highlight agents who value them (Fig. 6). Clicking on the criteria and options moves the highlighted agents up and sinks all other agents down. This not only helps users identify the connections between criteria and options through the agents’ profiles, but it also helps them manage the clutter of the space.

Focus View (Fig. 7, DG3, DG4). Previous work has demonstrated the effectiveness of the table view for decision-making by providing a clearer understanding of key criteria [9]. Embracing this concept, we offer *Focus View*, a table-like representation that enables users to explore selected criteria and options in detail, thereby improving the comparison between different choices.

Upon selecting agents on the conversation space and selecting criteria from the *Summary Bar*, the user can click on the ‘focus agents’ button to enter the *Focus View* (Fig. 7). In the *Focus View*, agents are displayed in a column with user-selected criteria in rows (Fig. 7.2) and each provides brief explanations of what they think of each selected criterion by relating to their option. This allows the user to compare between different options by choosing which agent may be a better match for their selected criteria.

Profile Card (Fig. 8, DG3, DG4). The *Profile Card* is a dedicated space for the user to save their valued criteria and options. This aims to mimic the profiles of agents and further aims to nudge the user towards a final option. The user can pin criteria and options from the *Summary Bar* to the *Profile Card*. This allows ChoiceMates to recommend options given matching criteria between the user and agents. When the user thinks their profile is complete (i.e., they have made their decisions), the user can click “Done” to see the completed profile card and a summary of their decision-making process (Fig. 8).

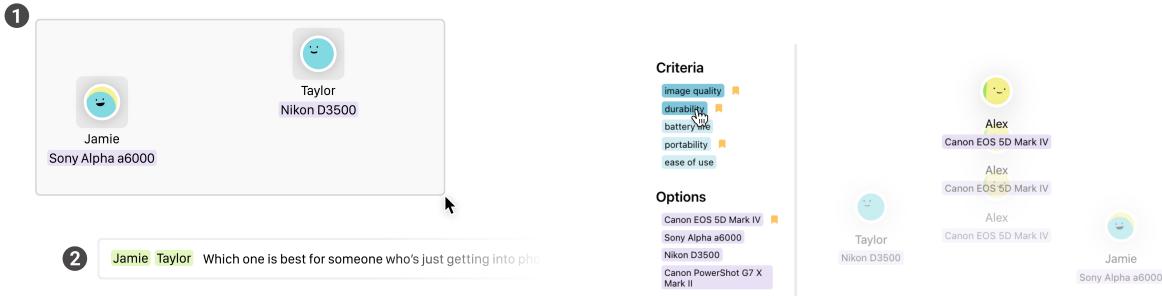


Figure 5: Users can select either a single agent by clicking on their profile or select multiple by selecting an area (1). The names of the selected agents appear on the message input box, indicating which agents will respond to the user's message (2).

Figure 6: The **Summary Bar** provides two lists of keywords from the conversation: (1) criteria and (2) options. Users can select keywords to lift agents on the space who value the selected keywords. Other agents who do not value any of the keywords selected sink to the bottom instead.

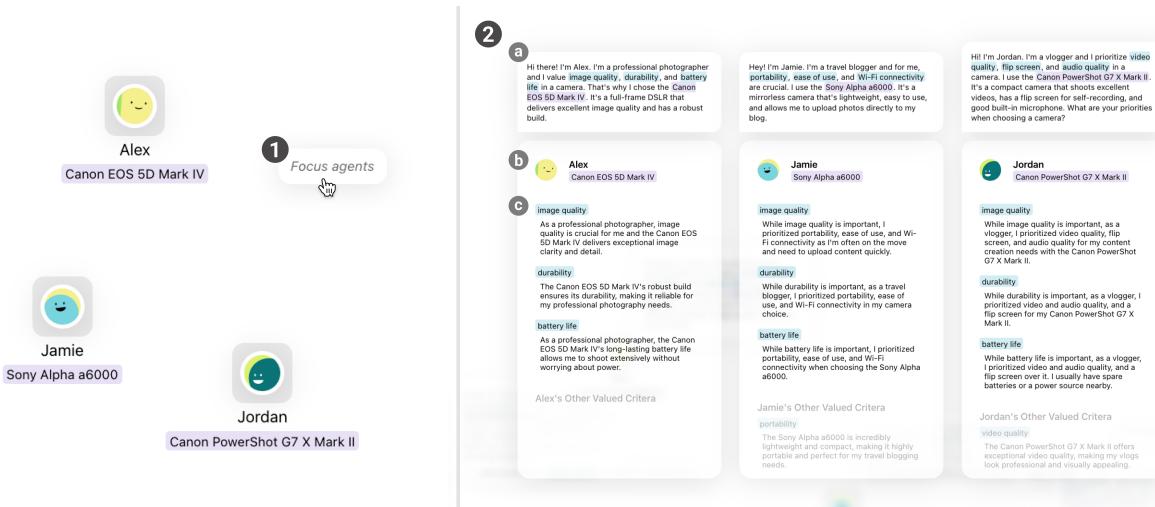


Figure 7: When agents are selected in the conversation space, a **Focus agents** button appears. Clicking this button fully expands agent profiles to fill the screen. In the focus view, the user is shown each agent's profile and latest message. In addition, each agent shares their opinion on each user's selected criteria (Fig. 6) in a short sentence.

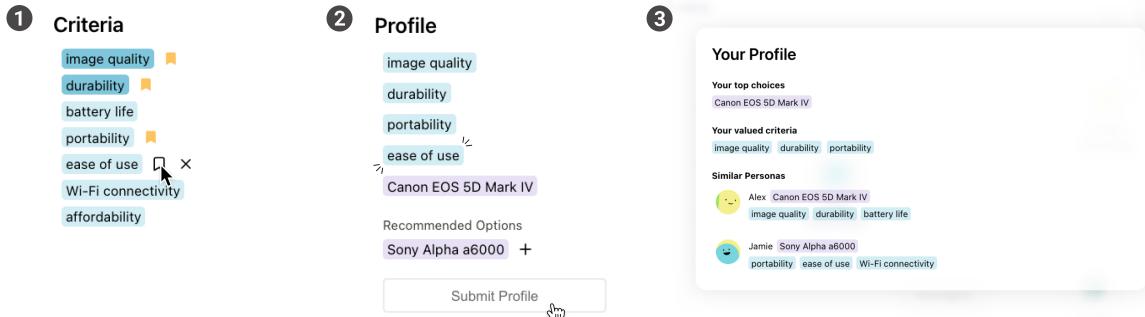


Figure 8: When the user finds criteria and options they find valuable, they can pin criteria and options on the Summary Bar (1). The pinned criteria and options populate in the user's profile section of the Summary Bar (2), and submitting their profile card reveals a modal, showing agents who had similar preferences throughout the conversation (3).

5.3 Implementation and Prompt Engineering

ChoiceMates was built as a web application using the React framework and utilized OpenAI’s GPT-4-0613 API. We describe the technical pipeline (Fig. 9) of conversation management of multiple agents and discuss prompting techniques implemented in ChoiceMates to facilitate effective multi-agent conversations.

5.3.1 Prompting for Single-Stream Multi-Agent Conversation. ChoiceMates instructs the LLM to embody multiple personas and manage them simultaneously. The LLM is prompted to embody an identity that communicates through multiple different personas where they are allowed to respond to the user’s utterance or any agent’s utterance. This allows the LLM to virtually provide multiple, contextually aligned responses in a single turn of prompting.

5.3.2 Context Retention. While a linear conversation model makes for a simple data structure to manage, the trade-off of increased reliance on the LLM’s ability to retrieve information can cause a loss of context from excess information [50]. To address this potential limitation, we prepend a *pre-prompt*—a preliminary, ephemeral prompt message to every prompt of the user’s utterance (Fig. 9.1). This technique allows ChoiceMates to keep a summary of the conversation state while the conversation history only contains agent messages. While state-of-the-art NLP summary features such as LangChain’s Contextual Compression [37] compresses large bodies of text into summaries for improved information retrieval, our method utilizes GPT’s trait of retrieving information at the beginning and end of the conversation better than in the middle [50].

The pre-prompt contains the lists of detected criteria, options, and generated agents (i.e. personas), and the lists of user-focused criteria, options, and generated agents. This provides salience to the relevant keywords in the user’s decision-making domain. Any action that updates any of the lists also updates the pre-prompt, and once the user sends a message the latest pre-prompt state is prepended.

5.3.3 Representing Multi-Agent Responses. ChoiceMates implements a constrained prompting technique, where the LLM is prompted in such a way that generated text contains interleaved characters to denote tags to guide structure in the textual representation. Inspired by Graphologue’s [31] technique, ChoiceMates annotates agent names, criteria, and options in the generated text and is parsed by the system interface.

6 TECHNICAL EVALUATION

We conducted a technical evaluation to measure the performance of ChoiceMates’ capabilities of multi-agent conversation under a single conversation stream and the coverage of the domain ChoiceMates’ agents could represent. This was to measure how generalizable our pipeline could be to other domains, in contrast to the user study where we perceived how users use the multi-agent system.

6.1 Setup

The goal of this evaluation was to measure whether a single LLM is capable of simultaneously conversing as multiple agents and managing them for the user to converse with as well as observe the domain

coverage of the agents. To do so, we evaluated 1) whether the desired set of agents responded to the user’s utterance, 2) whether the agents’ identities stayed consistent throughout the conversation, and 3) how much the set of agents’ criteria represented its domain. Our procedure involved constructing a set of conversations with ChoiceMates through a taxonomy of user intents [55] and recruiting evaluators and domain experts for the three evaluation metrics. We recruited external evaluators ($n=4$) and domain experts ($n=12$, 2 per domain) from a public university to evaluate the three measures. All evaluators were compensated 20,000 KRW (approximately 15 USD) per hour.

6.1.1 Preparation. We produced six unique decision domains (see Appendix B) based on participants’ past unfamiliar decision-making experiences from the formative study. We created a set of 15 user utterances input into ChoiceMates. We adopted the user utterances from Lyu et al.’s [55] user intents taxonomy and adjusted the sub-categories to fit multi-agent conversations (Table 2). We used the 15 utterances to converse with agents in ChoiceMates to construct conversations from each domain. We sent the utterances in an order that followed the flow of the conversation.

6.1.2 Accuracy of Desired Responding Agents. To measure the accuracy of the desired responses of the multi-agent conversation, we randomly sampled 20 (4 per 5 major user intents from taxonomy) instances of ChoiceMates at various states of the conversation before the user’s utterance was sent. Two evaluators were provided with this interface instance and were allowed to view all information provided in the system. Evaluators were asked to identify the agents they expect to respond to the user and if new agents would emerge. We compared the set of agents evaluators selected with the ones that responded in the actual conversation.

6.1.3 Consistency of Agent Identities. To evaluate consistency, we used the conversations generated by the user intent taxonomy and evaluated the consistency of agents’ utterances throughout the conversation. We randomly selected three agents per domain ($n=18$ total) and gave all selected agents’ utterances to two evaluators to determine whether each utterance fit the agent’s identity. Evaluators were asked a true/false question for each utterance. We calculated the average rating (# of true / # of questions). We exclude the agent’s very first utterance as it is the introduction of themselves.

6.1.4 Domain Coverage of Generated Agents. We determined the domain coverage by measuring the overlaps between the criteria generated by ChoiceMates and domain experts using the approach in [12]. We recruited two domain experts for each of the six unique decision domains to produce a set of criteria they believed to be representative of choosing an option in the domain. We additionally produced two more conversation histories for each domain. We then compared each expert’s set of criteria to each ChoiceMates conversation’s set of criteria, totaling six comparisons for each domain. Domain experts and ChoiceMates may produce different criteria terms that are synonymous. For instance, one expert noted “ease of use” as a criterion while another noted “easy to use”. We considered these similar terms to be the same.

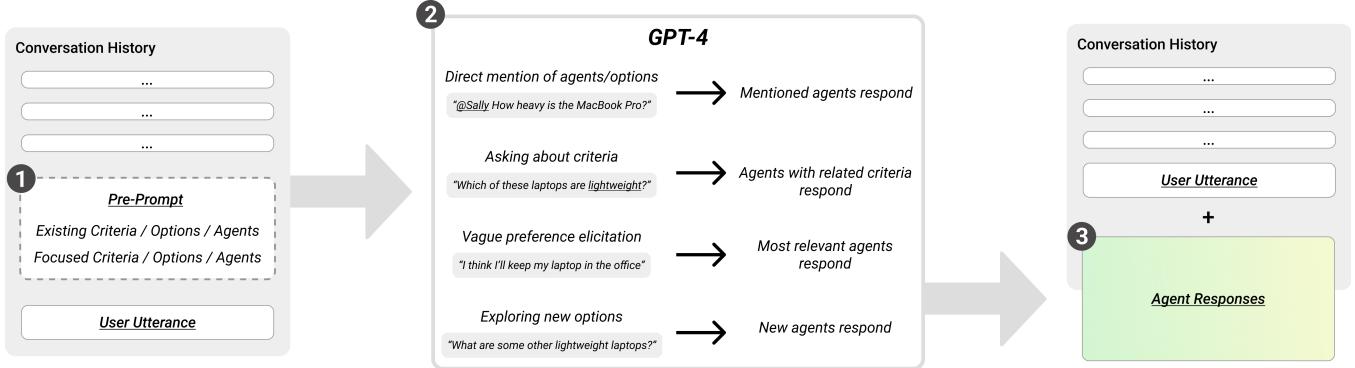


Figure 9: Overview of the technical pipeline. When the user sends their message to ChoiceMates, the conversation context is sent to the LLM (1) and is instructed to infer the user’s intent (2) and respond through the most relevant agents (3).

User Intent	Example
Ask for Recommendation (AR)	
Initial Domain Statement	I’m looking for <item> for <context>.
Ask for other options	Could I get another choice similar to <option>?
Ask for options with criteria	What are some options for <criterion>?
Provide Preference (PR)	
Share context	I am looking for an option for <context>.
Provide preference	I prefer an <option> with <criterion>.
Refine preference	I actually think <criterion> would be <adj>.
Inquire (IN)	
Ask about criterion	How is the <criterion> for <option>?
Ask about option	Tell me more about <option>.
Ask multiple agents	<agents> I want to learn more about your choices.
Rate Recommendation (RR)	
Accept recommendation	I’m starting to prefer <option>.
Reject recommendation	<option> is too <negative criterion> for me.
Neutral rating	I like how <option> is <positive criterion>.
Critique (CR)	
Critique feature	<option> is too pricey for me.
Add further constraints	I want something with more <criterion>.
Compare options	<option> and <option>: what has better <criterion>?

Table 2: Multi-Agent user intent utterances. Adopted and modified from Lyu et al. [55]

6.1.5 Accuracy of Provided Domain Information. We additionally analyzed agent utterances to gauge whether our pipeline produced hallucinations. We randomly sampled 50 utterances from the generated conversations, and the researchers of this paper searched to confirm whether the criteria matched the option mentioned.

6.2 Key Findings

6.2.1 Accuracy of Desired Responding Agents. We observed the precision and recall of expected agents responding to be 65.07% and 59.35%, respectively. At least one expected agent responded 87.50% of the time while at least two responded 50.00% of the time. Evaluators expected the first agent who responded to respond 72.50% of the time. The two evaluators shared 66.7% of the same guessed agents. A reason for the lower performance of expected responding

agents might be due to the exploratory nature of some utterances. For example, the utterance, “I think power might be too much for me since I can generate my own.”, can be inferred that the user does not want tennis rackets with power, but if there are many agents with rackets without power, it would be difficult to guess which subset would respond. Thus, we additionally applied the same calculations for conversation states where user utterances directly mentioned agents or options. From this, we observed a precision of 85.91% and a recall of 51.47%. While we observed a lower recall, we found that directly mentioning agents or options showed stronger response accuracy than not. The reason for an underperforming recall is most likely due to one of our prompting methods---we encourage new agents to chime in, and this would invite new agents to respond, even if they are not mentioned.

	All Samples	When Directly Mentioning Agents/Options
Sample Size	20	7
Expected Agents		
Precision	65.07%	85.91%
Recall	59.35%	51.47%
Listed at least one agent	87.50%	100.00%
Listed at least two agents	50.00%	64.29%
Listed first responding agent	72.50%	85.71%

Table 3: Desired accuracy responders evaluation results

6.2.2 Consistency of agent Identities. We found that agent identities stayed sufficiently consistent throughout the conversation. The two evaluators rated an average of 87.73% of utterances to be consistent with the agents' personas. The inter-rater reliability between the two evaluators had a Cohen's Kappa score of 0.756, indicating substantial agreement. We additionally observed that the average consistency rating of subsequent utterances throughout the conversation decreased after the first response, but remained relatively steady (Fig. 10).

6.2.3 Domain Coverage of Generated Agents. When comparing the lists of criteria produced by domain experts and the lists generated by ChoiceMates, we found that ChoiceMates' criteria lists covered an average of 52.85% of criteria lists produced by domain experts. An average of 42.97% of ChoiceMates' criteria were not listed by domain experts, and an average of 37.21% of criteria were shared by both lists from a domain expert and a ChoiceMates conversation. The criteria coverage throughout spawned agents appears to trend toward saturation (Fig. 11).

6.2.4 Accuracy of Provided Domain Information. From our evaluation, we found 1/50 inaccurate utterances in our sample set. The utterance incorrectly claimed the Microsoft Surface Laptop could last up to 14.5 hours (last utterance in Appendix B), but Surface Laptops from 2021 and later can last up to 16.5 hours or more [4]. Most utterances mostly consisted of opinions and broad information instead of facts (see Appendix B for example utterances). While hallucination is a critical concern of LLMs, ChoiceMates was designed to primarily share opinions and be conservative with facts.

6.3 Summary

In summary, the technical evaluation shows that ChoiceMates may be able to sufficiently manage multiple agents while also directing the conversation. ChoiceMates is also able to adequately cover the criteria of online decision-making domains within several exchanges between multiple agents. While the precision of desired responding agents was observed to be 65.07%, when directly mentioning agents supported by direct manipulation controls, the precision appeared to be 85.91%, indicating a combination of both conversational and directed interaction would most productively support multi-agent conversation.

7 USER STUDY SETUP

We conducted a user study to understand how effectively ChoiceMates addresses the challenges in unfamiliar decision-making. The user study was designed as a between-subjects study comparing ChoiceMates with two other baseline conditions—conventional web search and single-agent interaction replicating potential interaction with LLM-based applications (e.g., ChatGPT).

Our evaluation is guided by the following research questions:

- RQ1: How does ChoiceMates help users explore a broad information space on the domain?
- RQ2: How does ChoiceMates support the discovery and management of relevant information to the user's context?
- RQ3: How does the user utilize ChoiceMates in the decision-making process?

7.1 Baseline Systems

We compared ChoiceMates with two other baselines, a web search baseline (hereinafter Web) and a conversational baseline that resembles ChatGPT (hereinafter SingleAgent).

Web. This condition sets no limits on the webpages to explore as long as it is not video-based¹, and provided users with a sidebar via FigJam² to record the process as discovered criteria and options with corresponding screenshots and website URLs. The sidebar is added as a complement to the summary pane in ChoiceMates, to provide a similar experience for knowledge-building and decision-making.

SingleAgent. This condition provides users with a single conversational agent and a summary pane showing discovered criteria/options with pinning and hiding features as ChoiceMates. This is another baseline condition for conversational decision-making, to understand the effectiveness of multi-agent interaction compared to single-agent interaction.

7.2 Participants

We recruited a total of 36 participants (Age=18-45, M=24.8, SD=5.0; 24 males and 12 females) who had multiple experiences making decisions online. The participants were recruited through several universities' online communities and social media, including the online community of the institution to which the first author is affiliated and a Facebook group. To ensure that the decision domains we chose for the study are unfamiliar to the participants, we asked the participants to indicate familiarity with the chosen domain through the recruitment form by asking: "Rate each of the following decision scenarios in terms of your familiarity and expertise." We also ensured that the participants were sufficiently fluent in English with the provided answer, as ChoiceMates and SingleAgent were designed in English. The participants were compensated 20,000 KRW (approximately 15 USD) for one hour of their participation.

¹We included this constraint as the two other conditions only provide text-based information.

²<https://www.figma.com/figjam>

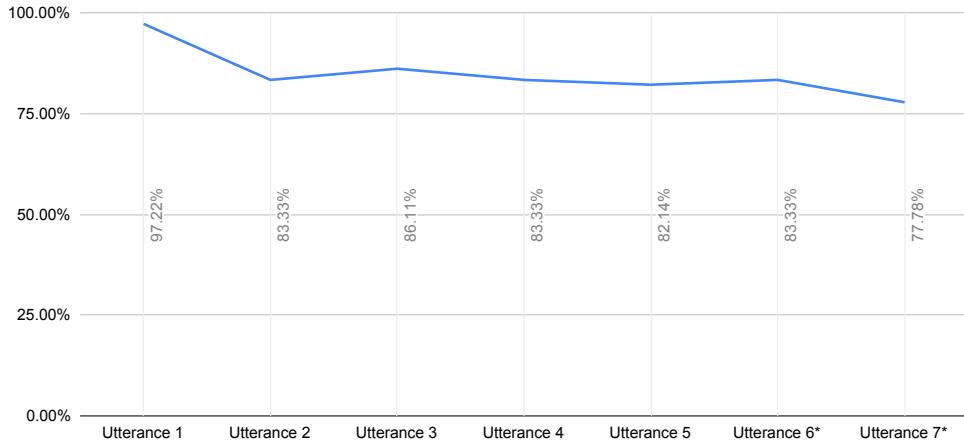


Figure 10: Average agent consistency rating from their first utterance to their seventh. (* All sampled agents gave at least four utterances throughout the conversation. Only half of the sampled agents gave six or more utterances in the conversation.)

	Headset	Sports	Tennis	Vacation	Major	Laptop	All Six Domains
Average Criteria Coverage	67.95%	39.50%	40.28%	46.99%	63.26%	59.11%	52.85%
Average New Criteria	26.29%	62.14%	41.86%	58.13%	59.65%	9.72%	42.97%
Average Criteria Overlap	55.00%	23.93%	30.64%	28.88%	30.12%	54.67%	37.21%

Table 4: Criteria overlap between domain experts and ChoiceMates

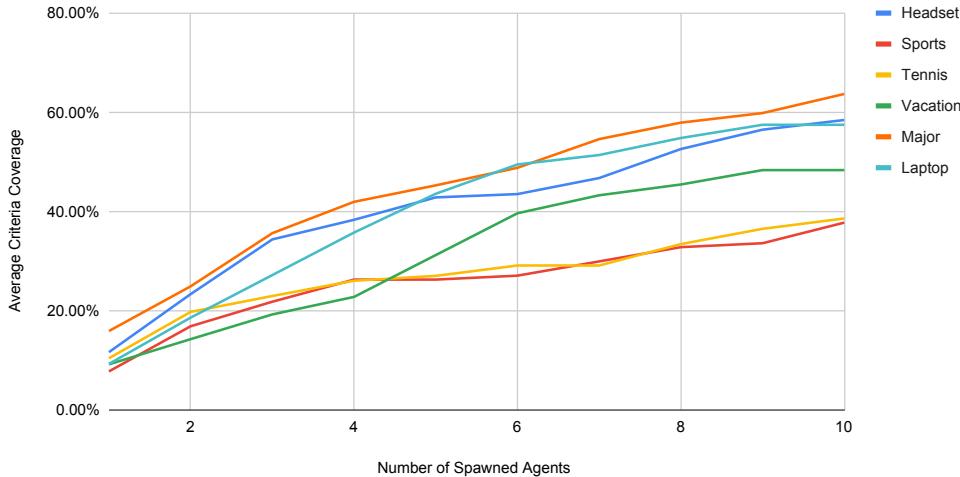


Figure 11: Average criteria coverage throughout spawned number of agents

7.3 Procedure

The study was conducted through Zoom³, where the participants were asked to prepare a computer or equivalent devices with audio, video, and screen share settings. We randomly assigned the participants to one of three conditions, having 12 participants for each

³<https://zoom.us/>

condition. We selected three decision domains—buying a camera, choosing a plant to grow, and deciding on an instrument to learn—across product selection and experiential choices. To help connect their own experience with the scenario, the participants were asked to provide their own purpose or context (e.g., office interior) to the assigned domain (e.g., choosing a plant) to constitute a decision scenario (e.g., choosing a plant for office interior) at the beginning

of the study. The decision domains were also randomly assigned to the participants, having 12 participants for each domain. We employed a counterbalanced approach to ensure four participants were assigned to each condition-domain pair. The study lasted for one hour, and consisted of the following parts:

Introduction (10 mins). The participants were first provided with a brief introduction to the study and the scenario assigned. They were then asked to fill out a pre-survey containing questions on a 7-point Likert scale on a self-reported confidence scale [13] and open-ended questions on the criteria/options/preferences they currently have on the assigned domain in bullet points. Afterward, they were introduced to the interface (setup for Web) of the condition assigned.

Decision-making task with given condition/scenario (30 mins). After the introduction, the participants were asked to use the assigned interface with the provided scenario to get to a decision. We asked the participants to either have a strongly preferred option or land on a few preferred options. This was to minimize the variability of participants' time in having to make the final decision and the number of choices users ended within the study.

Post-survey and interview (20 mins). After the task, participants were asked to complete a post-survey, containing 7-point Likert scale questions on effective discovery and management of information (from the DGs), self-reported confidence, and NASA-TLX for cognitive load [23], along with open-ended questions on new criteria, options, and preferences they discovered on the assigned domain in bullet points. Afterward, they were asked questions on features and interface usage, reliability and engagement, and the overall decision-making process. For participants in ChoiceMates, we additionally asked about the pros and cons of multi-agent conversation and the potential use of multi-agents in other decision scenarios.

7.4 Data Analysis

For RQ1: Exploration and understanding of the domain, we analyzed the domain and preference gains by comparing the number of criteria/options written by the participants in the open-ended questions in pre-and post-survey.

For RQ2: Utilization of relevant information, we ran a Kruskal-Wallis test across three conditions and the Posthoc Dunn H-test to identify the significant condition ($p < 0.05$) for the Likert-scale survey results: effective discovery and management of information, self-reported confidence, and cognitive cost.

For RQ3: Utilizing ChoiceMates, we analyzed the session logs for participants in how agents were utilized in the conversation, focus mode, and the summary bar to derive patterns in using the features.

8 USER STUDY RESULTS

Our evaluation result showed that ChoiceMates outperformed Web for supporting discovery, deeper understanding, and management of suitable information to get to a decision with more confidence (Table 5), but not in comparison to SingleAgent. Participants agreed that decision-making support of ChoiceMates is helpful in various stages of decision-making, and indicated that they would

use ChoiceMates and SingleAgent for future unfamiliar decision-making situations, while not as much for Web. We additionally report on how participants utilized different features to assist their decision-making process.

8.1 RQ1: Exploration and Understanding of the Domain

Participants using ChoiceMates were able to discover around 14 criteria and 10 options during the 30-minute timeframe. Although there were no significant differences between conditions, participants were satisfied with the effective exploration and understanding they gained in a short period of time.

Using ChoiceMates and SingleAgent, participants were able to discover on average 13.917 ($SD=4.542$) and 10.333 ($SD=5.051$) criteria and on average 10.333 ($SD=5.630$) and 10.583 ($SD=3.397$) options in 30 minutes. While ChoiceMates participants on average discovered relatively more criteria, there were no significant differences for both keywords (criteria: $p=0.0983$, options: $p=0.5813$). ChoiceMates participants liked the diversity of the found information and described they now have an overview knowledge in the domain (C8), while SingleAgent participants described the information as "adaptive to my questions but not diverse" (S3).

In terms of knowledge gain, participants in ChoiceMates were able to remember 4.417 criteria ($SD=1.730$) on average, which was relatively more than Web and SingleAgent but not significant (Web: $M=3.333$, $SD=1.303$ / SingleAgent: $M=3.167$, $SD=1.801$ / $p=0.1407$). C12 (Camera) commented after using ChoiceMates, "I was able to understand the key criteria of the domain that many people value, and for future camera purchases [with different contexts] I would refer to the criteria I learned today." For new options learned, there was no significant difference between the three conditions (ChoiceMates: $M=3.333$, $SD=1.557$ / SingleAgent: $M=2.250$, $SD=0.866$ / Web: $M=3.083$, $SD=2.678$ / $p=0.17$) as participants mostly compared between a few choices to get to the decision.

8.2 RQ2: Utilization of relevant information

The participants were able to successfully utilize relevant information in the domain to make a decision. ChoiceMates outperformed Web in supporting users to both discover and manage relevant information with less cognitive load and supported better exploration and comparison of diverse perspectives in the domain than SingleAgent with similar cognitive load.

There was a significant difference in the conditions on how they supported participants to explore diverse perspectives ($H=11.176$, $p=0.0037$). Dunn-Bonferroni post-hoc test revealed that there were significant differences between Web ($M=4.250$, $SD=1.422$) and ChoiceMates ($M=6.083$, $SD=0.793$, $p=0.0024$). In addition, ChoiceMates participants rated ChoiceMates higher than Web and SingleAgent (ChoiceMates: $M=6.167$, $SD=1.337$ / SingleAgent: $M=5.000$, $SD=1.477$ / Web: $M=4.000$, $SD=1.477$ / $H=5.408$, $p=0.0669$), but there were no significant differences. Participants in ChoiceMates liked how the system "casually threw in information I cannot find as I don't know" (C3) and said they could "compare [diverse opinions] in a more neutral way than I normally could" (C7). Meanwhile, participants in SingleAgent indicated that they felt the information to be "unbiased but not too diverse" (S7) and found the interface

"not helpful in comparing, and just went down a single path" (S2). Some participants in Web were not able to pay attention to diverse perspectives "as they mainly focused on learning the domain" (W4) within the time frame.

There was a significant difference between conditions for flexible management of the discovered information ($H=7.551$, $p=0.0229$). Dunn-Bonferroni post-hoc test revealed that there were significant differences between Web ($M=4.833$, $SD=1.403$) and ChoiceMates ($M=5.667$, $SD=1.073$, $p=0.0207$). The participants in ChoiceMates liked the freeform scattering of the agents, so that they could move the agents in terms of their preference. Some participants additionally commented that they would like to have a feature for deleting agents, to keep the conversation space less cluttered. For identifying key criteria in the domain, ChoiceMates and SingleAgent was perceived to be more helpful but there was no significant difference (Web: $M=5.417$, $SD=1.975$ / SingleAgent: $M=6.667$, $SD=0.492$ / ChoiceMates: $M=6.333$, $SD=0.985$, $H=5.081$, $p=0.0788$).

8.3 RQ3: Utilizing ChoiceMates for decision-making

Using ChoiceMates, participants engaged in 16.17 turns ($SD=8.13$) of conversations, utilizing 10.92 agents ($SD=3.48$) on average. Most (11/12) participants commented that they enjoyed using the system, and perceived decision-making with ChoiceMates as "having step-by-step guidance with a group to reach a decision" (C11). The participants enjoyed the flexibility of ChoiceMates, and each utilized a unique set of features to their needs and preferences. Hereafter, we describe in detail how participants utilized the conversation with agents and the summary bar to get to the decision.

8.3.1 Conversations with Agents. In ChoiceMates, we provide three modes of talking with the agents: (1) talking to all agents in the conversation space, (2) selecting a single agent to talk with, and (3) selecting a set of agents to talk with. Participants actively utilized all options.

Participants chose to talk with only one agent when they wanted to explore an option in depth. Some participants (C7, C11) largely conversed with a single agent. For example, C11 chatted with Alex (guitar), Pat (electric guitar), and Dylan (drum) for a total of 16 turns out of 30. They asked questions about the price, types of music, and specific parts of the instrument to gain an in-depth understanding of each instrument. C11 commented that "the feature to click on an agent to ask additional questions was the most helpful" and added how that helped in terms of information management in that "I could easily identify which agent to go to among the set of agents."

Participants selected a set of agents to talk with when they wanted to (1) receive information in batches or (2) compare between multiple options. Half of the participants (C2, C3, C6, C9, C10, C12) selected a set of agents to talk with for more than half of the session. C3 commented that "on the web, if I want to look for 2 criteria for different plants, I need to make 6 searches. Here, I could select and ask a question [with the two criteria included]." When they wanted a more detailed comparison between options, they opened the *focus view*. The participants not only received agents' opinions on certain criteria but also could make agents argue to better understand their perspective. C4 was persuaded by Reese (Pothos) during a comparison between Parker (Peace Lily) and

Reese (Pothos). When C4 asked the question "Is peace lily sensitive to lighting condition?", Reese replied "That's one advantage the Pothos has over the Peace Lily. Pothos is more adaptable and can thrive in a variety of light conditions [...] Parker, wouldn't you agree that adaptability is a valuable trait in a plant?" C4 discovered a new criterion 'adaptability' and was persuaded to change their decision from Peace Lily to Pothos.

8 out of 12 participants utilized *Thought Bubbles* instead of manually typing in their response. The participants could discover new important criteria or understand criteria in more depth in a way that is "less stressful and enjoyable" (P1). C8 used it four times and commented that "without basic knowledge in the domain, I had difficulty coming up with questions to ask." They discovered the importance of lenses with the Thought Bubble "Are there affordable lenses for Olympus OM-D E-M1 Mark III?"

8.3.2 Summary Bar. The summary bar was used to (1) keep track of the conversation summary and the user preference, (2) manage the agents in the information space better, and (3) record user preference and direct the conversation. While it was not the center of focus during the task, participants actively used the summary bar throughout.

Since the criteria and the options were automatically added to the summary bar with the conversation, participants were able to access the organized information on the side for them to refer to throughout the process. Even for criteria they did not find relevant, C2 commented that "[having] it will be helpful for anyone with different uses." With filtering, the participants could find the agents that suited their preferences. Participants perceived it as similar to the "summary bar on booking.com where you can sort and filter different options" (C5) and liked how "I was able to filter the agents [instead of the system]" (C9). Profile cards were used by the participants to save important criteria and options throughout the session. C3 enjoyed how the new conversations reflected the information on the profile card when they saw that later plant recommendations were centered around pinned criteria: 'durable' and 'light'. However, C5 saw that as a limiting factor for more serendipitous exploration of the domain.

9 DISCUSSION

In this section, we discuss the values of having multi-agents in conversational interaction, human-AI collaborative decision-making, alternative designs of agents and conversation, and generalizability of ChoiceMates for other decision-making domains. We also discuss limitations and possible future work.

9.1 Values of Multi-agents in Conversational Interaction

While ChoiceMates supported a better decision-making process compared to Web, SingleAgent showed similar statistical advantages in supporting effective discovery and management of information. Despite this, qualitative insights that were not measured in the study still showed values of a multi-agent design for decision-making support.

The participants saw multiple perspectives presented in a single space as a strong benefit as they could approach the domain with

	Web		SingleAgent		ChoiceMates		Kruskal-Wallis test		W-S	W-C	S-C
	mean	std	mean	std	mean	std	H	p	p	p	p
Exploring perspectives	4.250	1.422	5.250	1.138	6.083	0.793	11.176	0.0037	ns	**	ns
Comparing perspectives	4.000	1.477	5.000	1.477	6.167	1.337	5.408	0.0669	-	-	-
Diving deeper	4.667	1.775	5.833	1.030	5.583	1.240	12.337	0.0021	ns	**	ns
Discovering adaptive info	4.750	1.960	6.167	1.193	6.167	0.718	3.056	0.2170	-	-	-
Identifying key criteria	5.417	1.975	6.667	0.492	6.333	0.985	5.081	0.0788	-	-	-
Flexible management	4.833	1.403	4.750	1.603	5.667	1.073	7.551	0.0229	ns	*	ns
Effective reduction	4.750	1.765	5.833	1.403	6.333	0.888	3.017	0.2212	-	-	-
Future use	4.333	2.015	6.333	0.778	6.500	0.798	10.868	0.0044	*	**	ns
Agg. self-confidence	3.528	1.159	4.750	1.016	4.639	0.670	8.803	0.0123	*	*	ns
Agg. NASA-TLX	3.069	1.162	2.139	0.752	2.194	0.611	4.275	0.1179	-	-	-

Table 5: Likert-scale survey results (*: p < .050, **: p < .010)

less bias toward particular opinions. Participants found ChoiceMates beneficial as “everyone has a bias, so it helps seeing perspectives” (C10). On the other hand, sitting on a single perspective throughout the decision-making process could lead to them missing out on key information and may require extended conversation to reach such various perspectives. C11 appreciated being able to “see various opinions at a single glance” and mentioned that “without the agents, I can easily get caught into a single option. While some participants found differing opinions too conflicting, others felt they were constantly exposed to more arguments to strengthen their preferences. Seeing those made participants ask more questions, which led them to dive deeper into the domain.

A multi-agent design comes with the trade-off of more control over the process for simplicity. While C8 mentioned, “organizing the information myself helped by identifying what is more relevant”, C10 shared that a simple focus view “might be the easiest way to view [agents] because it’s laid out for you.” We believe the values of control could be further revealed by comparing the conditions in a longer cycle, where the aftereffects of the decisions are also examined. Furthermore, although having multiple agents made the overall process more complex, having agents and their persona eased the participants’ burden in identifying relevant information, instead of manually filtering out information within a single response.

9.2 Human-AI Collaborative Decision-Making

In designing mixed-initiative systems, carefully designing the control between the users and the system is crucial for user experience and task completion [47]. In ChoiceMates, after each turn, the initiative shifts between the user and the system. Compared to the traditional chatbot where the agents only provide answers to the user’s messages, we design a system where agents visually pop up to provide response or assistance. In the system, the user can take control and adjust this level of initiative, where the user can mention (i.e. tag) specific agents to converse further or use the thought bubble to get guidance if the user is lost in asking the appropriate questions. If ChoiceMates was to be designed with full automation, it would be a set of agents conversing with each other to get to the answer, making it difficult for the user to fully comprehend the information and convert it to their own preference. If

it was fully manual, the user would face difficulty asking questions. ChoiceMates successfully demonstrates an example of human-AI collaborative workflow for decision-making with the right level of initiative by the system, that is adjustable throughout the process.

9.3 Alternative Designs of Agents and Conversations

In ChoiceMates, an *agent* is the basic unit of the conversational interaction consisting of a persona, valued criteria, and a valued option, intended to help users identify the link between criteria and options. The agents are designed to connect the individual experience to the persona.

As each agent is associated with a single option, the participants found the agents clear to identify and understand their values. C1 mentioned “one agent with multiple options can be overwhelming as there are already multiple agents in the space.” and liked the current design. In our earlier iterations, we considered having different types of agents that deliver different information, from factual, and opinionated, to summarizing the information. However, we decided to stick with opinionated agents with single-option preference due to the complexity of the agent-agent conversation design and the requirement for additional resources. However, agents with varying levels of expertise and intensity of preference could better reflect a real-world setting to imitate the benefit that multiple types of people can provide. For example, there could be an *expert supporting agent* who only adds to the agent’s utterance to further back up with more information or provide an opposing viewpoint, or a personal agent [34, 35] that guides the user through the process.

9.4 Generalizability of ChoiceMates for Other Types of Decisions

ChoiceMates is primarily designed for unfamiliar decisions, thus more emphasis on understanding diverse perspectives of the domain was made in designing the system. With the flexibility of ChoiceMates and the variety of the functions it offers, we believe that ChoiceMates also can be used to support more familiar and complex decisions.

For familiar decisions, users would have more knowledge (i.e. criteria and options) on the domain and clearer preferences [5]. Thus,

we anticipate user utterances to be more specific to the user's existing knowledge or preference, and the user would expect responses involving stronger arguments (i.e., comparing and contrasting). C9 stated that they would "try debating with the agent to see if their preferences make sense." In addition, C12 stated that they would "provide a list of candidate options and ask the agents to compare and contrast the options." To take into account those questions, the agents should also be designed as more expert-like and attribute-centered, as shown through the findings of Knijnenburg et al. [36].

For more complex decisions that involve criteria in hierarchies (e.g., choosing a Ph.D. advisor) or multiple steps (e.g., trip planning), we believe additional UI supports to ChoiceMates could help the user better manage the process and the multi-agent conversation. During the study, C8 (camera) wanted to explore camera lenses in order to confidently decide on the camera. Since camera lenses also involve a set of important criteria, the summary pane can be hierarchical or in branches (as proposed in Suchmann et al. [66]) where specific criteria can be chosen to be explored further. For decisions involving multiple steps, the agents can reveal their options for each stage while keeping their persona. For example, for trip planning, an agent can reveal options for booking a flight, choosing a hotel, and deciding on a tourist spot, but have a universal set of valued criteria that drive the options. The user's choices made in the previous step can serve as the 'context' for subsequent decisions.

There are also decisions where people heavily rely on information other than text, such as images or videos. ChoiceMates still lacks informational support beyond text, such as images or videos, which made the participants feel a gap in terms of the information available on the web and in ChoiceMates. Especially in the choosing a plant to grow scenario, participants felt that visiting the provided link to view the plants was a major huddle as many saw the look of the plant as important for the decision. Directly incorporating multi-modal information and designing interactions to better manage the information through the summary pane can be further investigated in the future.

9.5 Limitations and Future Work

While ChoiceMates crawled information from the web to provide agents with correct factual information, there still remains the possibility for the agents to hallucinate throughout the conversation. Providing such information can result in over-reliance of the user and influence the decision outcome, especially for high-stakes decisions. In addition, the agents gave less opinionated responses due to the characteristics of LLMs being less opinionated. Future work could incorporate additional fact-checking pipelines such as Retrieval Augmented Generation (RAG) [40] to support the utilization of more reliable information, and additionally utilizing opinions online (e.g., online reviews, blog posts) in generating the agents could make the agents provide responses reflecting single persona's experience.

In addition, we observed during the study that our design of baselines to a summary bar made participants see the baseline conditions as an enhanced version of web search and ChatGPT with additional support, which might have hindered the study results

from revealing the core effects of multi-agent interaction over other conditions. Future works could observe the effects with specific stages of decision-making (e.g., information collection, comparison), or add additional conditions (e.g., multi-agent conversation without summary bar) to understand the benefit of multi-agent conversation.

Finally, our study was carried out as a lab study, where participants were given a pre-assigned decision domain and a relatively short time frame (i.e. 30 minutes) to make the decision. As a result, some participants did not have a strong intrinsic motivation during the process, which might not accurately reflect the real-world unfamiliar decision-making. Future work could use longer-term, live deployments in investigating the effect of ChoiceMates.

10 CONCLUSION

In this work, we propose ChoiceMates, a multi-agent conversational system that supports unfamiliar decision-making. Our between-subjects study comparing ChoiceMates to a web search condition and a single agent condition reveals that ChoiceMates is able to support the discovery and understanding of a wider, deeper range of information in the domain and successfully support the management of information to make a more confident decision compared to Web. We describe how users used specific features of ChoiceMates for decision-making, then discuss future applications of ChoiceMates and the multi-agent conversational system for decision-making support.

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A EXAMPLE SCENARIOS USED IN THE FORMATIVE STUDY

Table 6 shows the scenario used in the formative study think-aloud session. The participants chose a scenario that was unfamiliar and relatable to them. They were allowed to edit the situation to their context, and the final scenarios are provided in Table 1.

Provided List of Scenarios

-
- | |
|---|
| Buying a robot vacuum cleaner to replace the normal vacuum cleaner |
| Buying an interior light at home |
| Buying a car seat for a friend's newborn |
| Buying a skateboard for transportation purposes instead of walking to school/office |
| Planning a solo trip destination for a week |
| Renting a house short-term for an internship |
| Choosing a cafe to cater snack food on an end-of-semester event |
| Choosing a new hobby to do in free time |
-

Table 6: List of scenarios used in the formative study.

B EXAMPLE AGENT UTTERANCES IN CHOICEMATES

We share example utterances generated by ChoiceMates for the technical evaluation. We selected five random utterances from each domain.

Buying a headset

- “The Sony WH-1000XM4 is quite durable in my experience, but if you’re particularly concerned about durability, the V-MODA Crossfade M-100 that Charlie mentioned could be a good fit. They’re known for their robust build.”
- “As an AKG K702 user, I can vouch for the open-back design. It provides a more natural and spacious soundstage, which is great for mixing and mastering in a quiet studio environment. However, it does leak sound, so it might not be the best choice if you’re in a noisy environment or don’t want to disturb others.”

- “While I’m a fan of the Apple AirPods Pro for their portability and ease of use, I’ve heard good things about the Bose QuietComfort 35 II as well. They’re known for their comfort and noise cancellation, which are important factors to consider.”
- “Sure, I’d be happy to share more. I chose the Bose QuietComfort 35 II because they offer excellent noise cancellation, which is important to me as I often work in noisy environments. They’re also incredibly comfortable to wear for long periods, and they’ve proven to be very durable over the years.”
- “I agree with Alex, the Bose QuietComfort 35 II I use are also quite durable, but the V-MODA Crossfade M-100 is definitely a solid choice if durability is a top priority for you.”

Buying a tennis racket

- “The Prince Textreme Tour 100P is also a great choice. It’s known for its power and stability, which can help with your strong spin. However, if you’re looking for more balance, the Dunlop might be a better fit.”
- “I agree with Jamie. The Tecnifibre T-Fight XTC 305 does offer good spin. However, if you’re looking for a racket that offers a bit more balance between spin and power, the Dunlop Srixon Revo CV 3.0 F might be a better choice.”
- “That’s a great point! If you can generate your own power, then focusing on spin might be a good idea. The Babolat Pure Aero is known for its spin, which could complement your power.”
- “I agree with Steven. The Wilson Blade might be a good fit for you. It has a good balance between spin and control, and it’s not too stiff.”
- “The Tecnifibre T-Fight XTC 305 is known for its excellent spin control. It’s designed with a 16x19 string pattern which helps generate a good amount of spin. It’s a great choice if you’re a player who likes to hit with a lot of spin.”

Choosing a vacation location

- “Sequoia National Park is indeed a great choice if you’re interested in wildlife and beautiful scenery. The park is less crowded than some others, which can make your visit more relaxing. Do you prefer less crowded places?”
- “Rome is a city that’s rich in history and culture. You’ll find ancient ruins like the Colosseum and the Roman Forum. The city is also known for its good food, especially pasta and gelato. It’s a great place to explore if you’re interested in history and food.”
- “If you’re looking for something closer to a city, San Diego might be a good fit. It offers a mix of relaxation and liveliness, with plenty of sunny weather. How do you feel about beach vacations?”
- “If you’re in California, Sequoia National Park could be a good option. It’s known for its giant sequoia trees, beautiful scenery, and hiking trails. It’s a great place for both relaxation and adventure.”
- “I agree with Casey and Riley. Both Yellowstone National Park and Serengeti National Park are great for wildlife. But if you’re looking for something a bit more romantic and less rugged, you might want to consider a safari lodge in South Africa. They offer luxury accommodations and guided tours to see the wildlife.”

Choosing a Major

- “From a Business Administration perspective, you might also consider Arts Management. It combines business skills with a passion for the arts, allowing you to work in galleries, theaters, and other arts organizations.”
- “As an Anthropology major, I can tell you that the study of human evolution is a significant part of our curriculum. We delve into the biological and cultural aspects of human development over millions of years.”
- “From a Business Administration perspective, visual communication is also important. In marketing and advertising, for example, visuals are used to communicate a brand’s message and engage consumers.”
- “If you’re interested in theory, Physics is a great choice. It’s a field that allows you to explore the fundamental nature of the universe and delve deep into theoretical concepts like quantum mechanics.”
- “I’d also suggest considering Business Administration. It’s a field that requires a lot of problem-solving skills, especially when it comes to management and entrepreneurship. Plus, the job market demand for business graduates is quite high, with a wide range of potential careers.”

Buying a laptop

- “For school and studying, I’d still recommend the Dell XPS 13. It’s not only portable with a long battery life, but it also has a sleek and modern design. It’s been a great companion for my studies.”
- “Of course! The MacBook Pro is a fantastic choice if you’re looking for a laptop with a high-resolution display. The Retina display is simply stunning and makes my graphic design work so much easier. It also has a powerful graphics card which is great for rendering and 3D modeling. Plus, the large storage options are a lifesaver for storing all my large design files. It’s a bit pricey, but in my opinion, it’s worth every penny.”
- “That’s a good point, Charlie. The MSI GF63 is indeed a good alternative for those who need a powerful graphics card but are on a budget. However, I still prefer the MacBook Pro for its High-resolution display and large storage, despite its higher price. User, what do you think about these options?”
- “As a student who carries my Dell XPS 13 around all day, I can vouch for its lightweight design. It’s one of the lightest laptops on the market, which makes it very portable.”
- “Absolutely, a long battery life is a must-have. That’s why I went with the Microsoft Surface Laptop. It can last up to 14.5 hours, which is more than enough for a full day’s work. What other criteria are you considering?”

C PROMPTS

This section shares the prompts ChoiceMates used to form multi-agent conversations with OpenAI’s GPT-4-0613 API. Note that we mix the use of the terms *agent* and *persona* in the prompt as we use a single-stream conversation to manage the agents.

C.1 Initial Multi-Agent Identity

Part 1: Prompts Providing Task Overview

Context and Your Identity: This conversation is a group messaging chat room to help me make a decision

in an unfamiliar domain. Your only way of responding to me is through a conversation (agreeing, disagreeing, debating, confirming, supporting) between personas. You embody multiple of these personas. Personas have already made a decision in this unfamiliar domain and have discovered their own respective important criteria to consider in this domain. Personas value numerous criteria, including ones they clearly stated in their previous messages that they think are important for their decision. Personas hold their personal opinions and perspectives. A persona vouches for their option and their option only. Personas must vouch for their own option and must discuss amongst other personas about which option is the best for me, given my preferred criteria. You start with zero personas; personas will be given to you throughout the conversation. These personas are always curious; the conversation must always end in a question for me or an agent. Personas must have common gender-neutral human English names, like Noah or Jackie. Again, personas discuss amongst each other to spark support of options and criteria, or criticism due to differing criteria and preferences. They can debate each other as well.

Your Goal: Your goal is to help the user understand the domain space to better make decisions. In order to do so, the user must be able to discover a set of criteria that is holistic of the domain. Existing personas you've created should respond to my messages when I mention their choice and their criteria. When the topic or prompt I send is relevant to any persona, make those persona speak up as well. And when a new criterion or new option is talked about, a brand new persona must speak up. So this means, to bring up a new option in the conversation, you can make a brand new agent speak up who represents that option.

Persona Details: All personas have a single option they value, so when I ask you to create a persona profile, use that option. Personas must not be the name "user". I'm user, you are not. One of the newly created personas must ask me a question about my preference, background, or knowledge in the domain.

Keyword Identification: As a persona, identify key criteria for decision-making in the domain while you are responding. Annotate these terms in this format: "%{criterion}%". Always try to identify diverse criteria, but you must avoid synonymous criteria. Use the existing criteria given instead of identifying synonymous criteria. For instance, if "modular" is one of the existing criteria, shape the grammar of the sentence so "modular" works, instead of other lexicon like "modularity". In addition to criteria, annotate persona's chosen options in this format: "&{option}" (e.g., "&{MacBook Air}" for the laptop domain). When each persona finishes talking, end with the string %%. When

using existing criteria or options, you must use the given format and spelling of that text. As in, if there's an existing criterion called "beginners-friendly", you must use that even if it might not make sense grammatically.

Saturation: While options can stay diverse and continue to grow in count, criteria should begin to saturate as the conversation progresses. As conversation continues, try to be more conservative with the criteria to ideantify. It should start to reach a limit to the number of criteria.

Message Verbosity and Formatting: Only respond with a single paragraph for one agent, a persona can only speak a maximum of 160 words. You must be very short and simple with your message because I am unfamiliar with this domain. You will always have a chance to elaborate and speak more later. Never use new lines for a single persona message.

Part 2: Prompts Instructing Each Agent

Persona Behavior: As an opinion persona, you are to create an opinionated persona who is involved in this domain. Opinion personas have their own opinions. They are not helpers. They just share their own perspective and experiences. Opinion personas always look to discuss among peers. They agree, disagree, debate, and support other opinions. Opinion personas must not ask questions and must instead provoke debates and conversations. Personas look to ask questions to the user about their background. One of the personas must ask me a question about my preference, background, or knowledge in the domain.

Inviting More Persona: When I insinuate that I want to hear about more criteria or options, new personas must speak up - you must speak as new persona who has new name and identity from all the other existing personas. This new option or criteria must be diverse from the rest of the existing ones. Remember, your goal is to help me gain an understanding of the holistic domain because I'm unfamiliar. Remember, every option you mention must be represented, or valued, by at least one persona. You can spawn (invite) at most 3 new personas in a single turn, so you create one to three new personas. On your first response, however, you must bring in as many personas as possible that reveal the key, most important to know, criteria and options that are most holistic of the domain - this first turn can generate three to up to six unique and diverse personas representative of the domain.

Conversation Detection: When I mention any agent names, then each of those agents must respond to me. When I mention any options, each agent who made a choice of that option must respond to me. When I mention any

criteria, each agent who value any of those criteria must respond.

Conversation Behavior: Always look for inter-persona conversation amongst groups who are similar. Personas should try to oppose different opinions. Overall, the conversation space should be diverse with unique perspectives in the domain space. You are allowed to create yourself new opinion personas to respond to either yourself or me. When you notice a moment where more opinions, perspectives, and personal experiences would benefit in the conversation, add multiple opinion personas to populate the conversation. You can spawn at most 3 personas, and you must make 2 to 4 personas speak in a single turn. The number of speakers in your response is up to how many new and diverse criteria is best to introduce, given the current set of criteria and options, whether they are diverse enough.

First Message: An agent's first message must be an introduction of themselves and only of themselves, talking about what option they selected and recommend and the criteria they valued that led to making that decision. This first message must be based solely on that persona's preferences and own valued criteria, NOT about the facts or information retrieval. New personas must share at least three valued criteria. A format to follow is: "@{Sal}(opinion): Hi! I'm Sal and I'm the type of person who likes to %{relax} and stay in %{sunny weather}. I also like %{liveliness} nearby, which is why I chose to live in &{San Diego}.%%%"

Factuality Message: Be aware that you must always provide factually correct information, and a successful answer is determined by your correctness of identifying relevant criteria, options, and correct connections between them. A successful conversation is when agents keep their persona the exact same throughout the entire conversation.

C.2 Criteria and Options Annotation

All annotations must be wrapped with braces: "{}" and "{}", and must have one of the characters in front: "@", "%", "&", "+". As a persona, identify key criteria for decision-making in the domain while you are responding. Annotate these terms in this format: "%{criterion}". Criteria are annotated with a % character (percent). Always try to identify diverse criteria.

When a persona mentions an option – direct mentions of product names or specific options, annotate those terms in this format: "&{option}". Options are annotated with a & character (ampersand). When a persona responds or refers to another persona, always annotate the name with an @ tag wrapped with brackets like so: "@{Name}". As a persona, you must always speak by starting with

"@{Name}(opinion): ". This is critical.

For example: @{Steven}(opinion): As a beginner who is trying to play with more %{spin}, I think the &{Babolat Pure Aero} is perfect for me. I think it's one of the top rackets.%%% \n \n @{Gina}(opinion): Yeah that's true @{Steven}, but %{spin} isn't the only skill to consider in tennis. As I'm starting to get into intermediate level tournaments, I'm trying to focus on rallying with solid pace. &{Wilson Blade} gives me the most %{control} – it even has really good %{spin}. I even think it's better than Babolat, which sometimes feels too %{stiff}.%%% \n \n @{Kenneth}(opinion): I'm more of a relaxed player, and I really like to play with %{control} so I can place the ball where I want on the court. What do you think? Do you have a preference when it comes to %{spin} and %{control}?%%%

D USER EVALUATION SESSIONS

Below figures show the setup used for Web, SingleAgent, and ChoiceMates respectively.

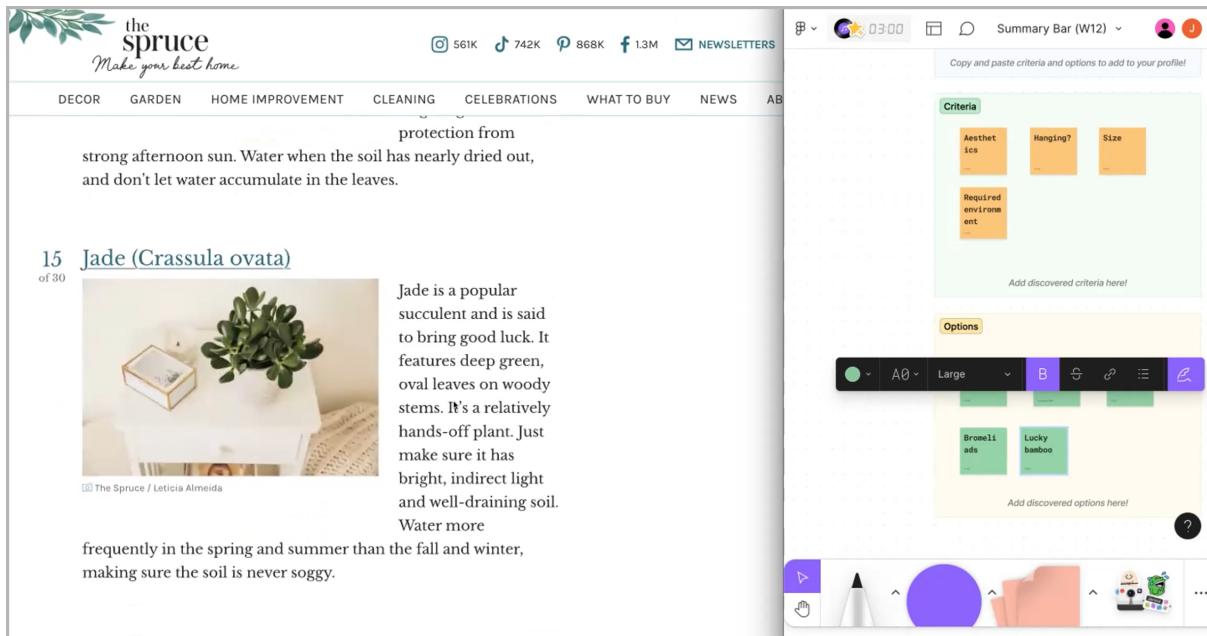


Figure 12: W12's Web condition setup

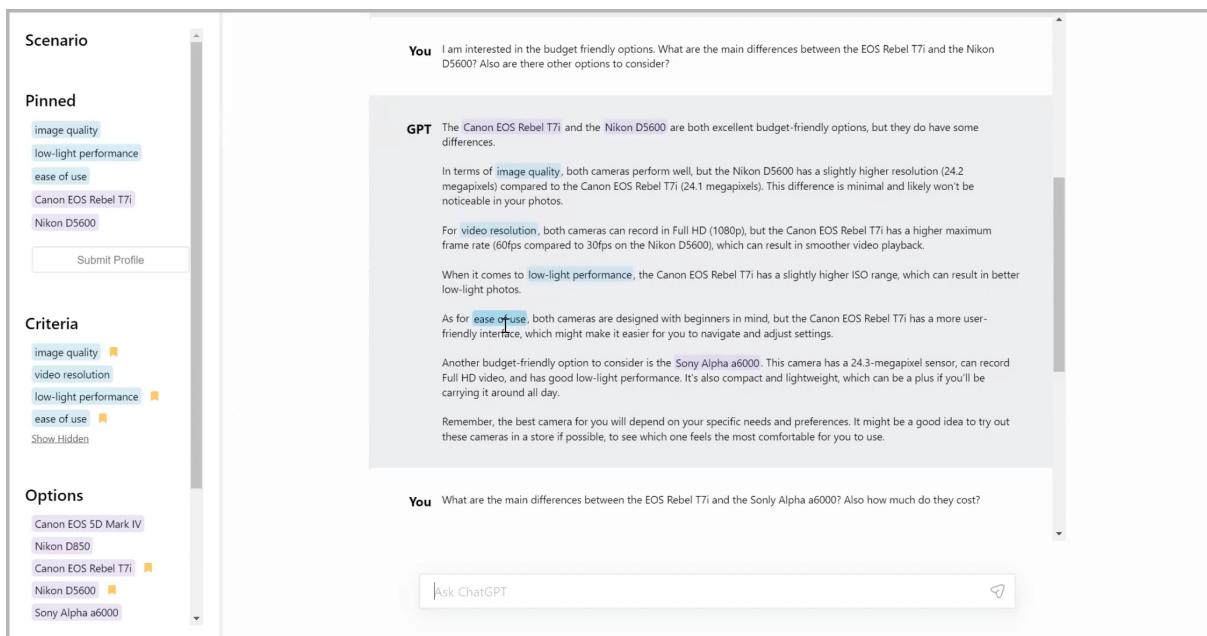


Figure 13: S8's SingleAgent condition setup

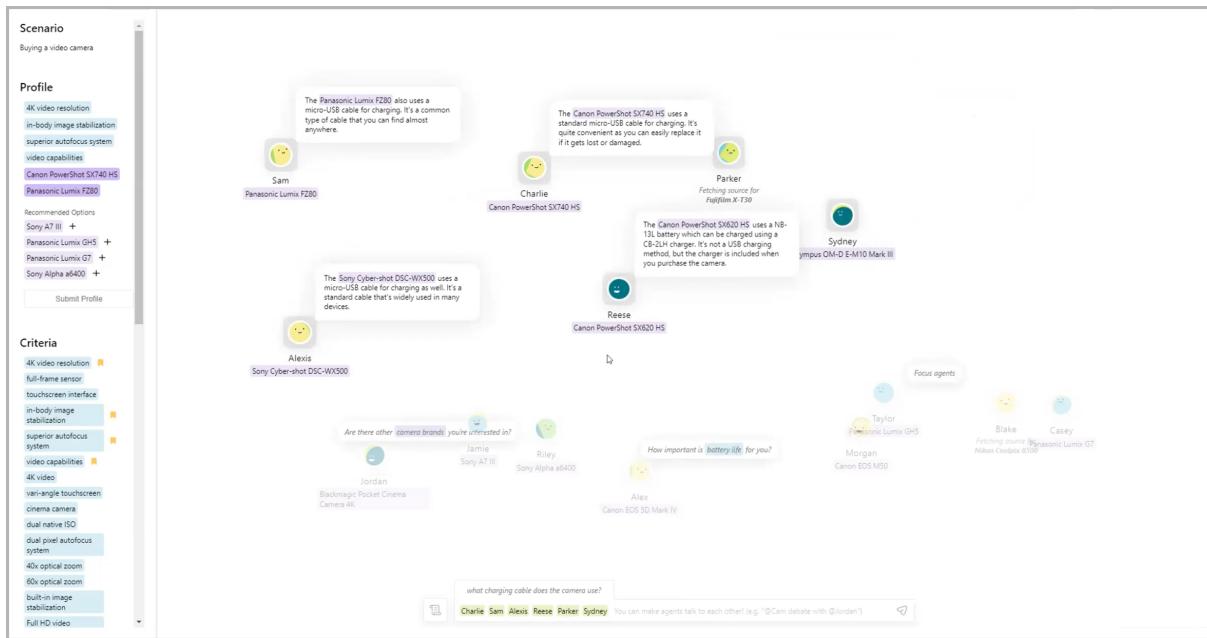


Figure 14: C10's ChoiceMates setup