Designing a Conversational Agent for Education using a Personality-based Approach

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***Abstract*—Conversational agents (CA) for education are the dialog systems that can interact with students intelligently. They are gaining popularity because of the potential benefits of education. However, there is very little research focusing on personality-based educational CA design. Therefore, we designed and built a high-fidelity educational CA prototype with four personality dimensions via Juji. This personality-based UX design supports the interaction between the CA and diverse users with eight personality styles within four dimensions. During the analysis and design phase, we extracted the keywords, attributes, distinctive behaviors, and interaction expectations to streamline the literal description of personalities into concrete design guidelines applicable to the prototype. The design guidelines were generated based on the extraction to specify interaction features, user expectations, and potential behaviors or actions that should be avoided. Based on the guidelines, we further developed four personality-based design logic in this integrated prototype. This work provides design guidelines for future user personality-based educational CA design. Moreover, the design is among the first group to provide four personality dimensions of design logic in one integrated prototype to better serve students. It sheds light on the future development of human-centred personality-based AI design in the industry while most chatbots are still rapidly developing.**

Keywords*—*Conversational agent/chatbot; personality-based UX design; human-centered AI

I. Introduction

Artificial intelligence (AI) is growing to take more responsibilities in society. Amongst a wide range of applications for AI, conversational agents (CA) or chatbots are inevitably becoming popular considering their purpose of serving people. Recent studies have analyzed CA's characters to categorize them [1]. Since CA's main functions are designed to retrieve information, analyze data, and assist human decision-making, human-centered design is the proper approach [2].

Pioneer educators are using intelligent educational systems in education [3, 4, 5]. Groups of designers are still developing different conversational interfaces to help students and educators retrieve information and make decisions. While most research has been done to study how to simply support students' learning as a whole [4, 6,7], our study aims to promote the concept of designing CAs on a user personality-based approach. We designed and integrated four CA prototypes that address interaction with eight personality styles introduced in Hogan and Champagne's (1985) research [8]. We aim to provide user-centered design guidelines for educational CAs, specifically focusing on college students' diverse personalities so that CAs can provide equitable service to students. We also provide detailed design examples interpreted from Hogan and Champagne's (1985) theory for future CA design to better serve diverse users with different personality styles [8].

II. Related Work

A. *Successful Cases and Error Handling of CAs in Education*

Traditionally, one advantage of online learning over face-to-face education is audience coverage. However, this comes with the cost of insufficient interactions between students and educators, and therefore relatively poorer learning outcomes. CA is one possible solution to this disadvantage through providing individual interaction with students. To test the applicability of using CA in online learning, a research team created a CA and evaluated it in associated lectures. Through the evaluation of learning outcomes from 182 participants, the CA is guaranteed to have significant value in improving learning outcomes. This study provides valuable examples of successful implementation of CA for an educational cause that can be followed and studied in future design [9].

Another successful example of an educational conversation agent was constructed to support software engineering learning and coding skills. By identifying the major requirements and unifying teaching practices, Hobert was able to design and evaluate his teaching assistants that support students with the capability of consulting, programming tutoring, and submitting. His study provides valuable experience for other parallel user cases in programming. However, this study only targeted the beginning level of programming. The design was not promising for learning assistance in situations where access to educators is limited or absent. Theories and experiences documented from this study can be re-examined to guide future development and study of educational CA [6].

A teacher is not always available in all cases of education. In before-class learning of software testing or other situations where an accountable educator is absent to learners' questions, CA is one of the possible solutions that requires no additional human resources. These demands of self-learners serve as the motivation for Paschoal et al. (2019) to investigate the viability of implementing CA as an online tutor. The research contains two aspects, to evaluation of CA-generated answers to online courses and applicability as a learning assistant. The result suggests that this assumption is acceptable and applicable as self-learning guidance [10].

Moreover, to cover the shortage of tutoring resources in online learning, Song et al. (2004) developed a human-imitated conversation system. This system contains several modules that process the conversation from user input to system responses.

The simulation of the human tutor is empowered by natural language processing techniques. More importantly, this system is designed with minimum changes to existing tutoring materials and reuses some of the features from AutoTutor, which reduces the cost of development [11].

Tan's research team also aims to use CA to help undergraduates in mathematical learning. They introduced an experimental design to students and collected data from the follow-up questionnaires. The result from students reveals the positive effect of using CA to help in learning. Though this study may not apply to all undergraduate subjects, they believe it does provide valuable experience and suggestions for future developers and researchers on educational CA design [12].

However, we are far from perfect with the current CA design and therefore left space for errors. (Aneja) Five categories of errors have been organized. Each of them may lower human expectations and fail in human simulation. It is worthwhile for future designers and developers to pay attention to these errors and address them in CA design to provide a better user experience. As a support to other scholars, they have the dataset released for people to study and utilize academically [13].

Recognition errors are unavoidable with current technology and vital to user experience during interaction with CAs. Therefore, exception or error-handling skills significantly influence the ability of CAs. Oviatt et al. (1998) discovered three patterns of how people resolve errors. Participants will increase parallel linguistic statements and repeat correction steps. They may also extend over phrases and pauses and rely more on the overall meaning of the speech. They also reframe their input to reduce linguistic variabilities. All of these discoveries aid in enhancing the performance of AI and adaptation modelling [14].

B. *Non-traditional CA Design in Education*

Educational CAs are being viewed with the potential to revolutionize the education model we have had for centuries. Possessing expectations of high-quality performance that matches with traditional education style, numerous obstacles remain unsolved. Targeting project-based learning, Kumar's team initiated a study that systematically examined the possibility of improving learning outcomes based on teams. The experiment of two groups with a pretest-posttest design results in proof of the influence of educational CA over individual performance and indirect influence on team performance. This work adds to the knowledge base of educational CA design theory and strategy [5].

Conversational agents for education are highly applicable and necessary. Even though a general-purpose CA may satisfy the basic demands of users, it is not enough to help users meet their academic goals. A task-oriented design was presented and proved to be effective through implementation. The result provides evidence of the positive influence on learning outcomes by the CA in such a design. It provides designers and educators who investigate CAs specifically for educational purposes a start and direction to follow in the future [15].

Researchers are investigating a way to improve learning experiences for learners. Cai et al. focused on enhancing interactions in math courses. They performed three studies that observed user preferences between chatbots and traditional online learning (videos/lectures), the learning outcomes, and learners' needs. These results have been collected and analyzed to provide a personal learning experience for users in the following learning process. Contextual bandits had been applied to the design of the chatbot which suggested greatly improved the performance and increased learning outcomes. This research emphasizes the direction of personalized learning and the significance of data-driven frameworks in the design of educational chatbots [3].

C. *Knowledge Base and Natural Language Processing in Educational CAs*

Knowledge base management is important to chatbot design. A good knowledge base design can benefit users in information accessibility. The researchers designed a model to manage the knowledge base of a chatbot, aiming to help students access the knowledge of specific courses. This design allows a chatbot to take the role of a tutor to provide the required knowledge to students and enhance their learning experiences. The chatbot classifies user queries into different categories and extracts the related result from the knowledge base to provide a reply. The result and expert evaluation suggested that the proposed method worked effectively in retrieving knowledge and was helpful when working as a tutor to students [16].

Targeting user knowledge during a conversation could be one of the solutions for the finer design of CA. An et al. researched to discuss the influence of user knowledge on the interaction with CA. A recipient-centered design is proposed by the research team that significantly reduces conversational correction during the interaction. This methodology is then implemented into their CA and provides productive results [17].

Hussain et al. (2023) also introduced a prototype that embeds chatbots in specific courses to provide students with academic support. The research covers a system that processes natural language, question recognition, and generating answers from its knowledge base. A test of this system has been provided to demonstrate its functionality. This study explained how specialization of the database will improve student learning experience and outcome, and shed light on further chatbot design [7].

Most of today's chatbots are still using conditional conversations like if-then to process interactions. Kasthuri and Balaji (2023) introduced a new memory algorithm to enable the chatbot to handle a more complex conversation. This is a significant improvement in the performance of chatbots over language processing [18].

Researchers also designed a new style of conversation approach to focus on task performance and information queries. The research stated the shortage of traditional dialog style with a single dominant party in educational CA, in which the learner is much less motivated in the learning experience. Therefore, letting the bot and user selectively take turns as the dominance of communication will be a good option. The CA will be more active and engaged with the role of educator to better help in learning. This design and dialog style is vital to educational CAs in making improvements to learning experience and outcomes as it will expand the depth and width of interaction in the learning process [19].

D. User-centered Design

Using a chatbot to support learning can be one of the trends in modern education. The researchers introduced a tutoring agent that can sense user cognition and emotions during the interaction. It enables a user to start learning by participating in trialogues (interacting with two agents simultaneously) to support learning. By playing a different role in the interaction, the chatbot's service is more flexible. The trialogue design provides a new direction of how to construct the interaction with the human learner and how the chatbot provides a more appropriate style of learning for users [20].

Clark et al. (2019) criticized the methodology of emulation over speech patterns in the CA design process for lacking encapsulation during the conversation. They launched research to investigate the criteria of a good conversation in participants' value and the possibility of implementation. Ultimately the research results in the polarization of socialization and functionalization to human-computer interaction, which reveals the essence of utilitarianism. This also leads to the final decision to reconsider our recognition of CA interactions [21].

E. Ethical Concerns

The adoption of new technologies such as CAs is also a concern. It is quite necessary to understand what advantages a new technology or research builds upon the previous foundations or traditional ways. The possibility of replacing search engines with chatbots requires comparisons and analysis of the data on the learning outcomes of learners. Therefore, Han and Lee (2022) constructed an experiment that compares FAQ chatbot users with FAQ webpage users within two online courses. The result of the experiment suggests that FAQ webpages are more accepted than FAQ chatbots. The reason for chatbot users to rate the experience lower than webpage users consists of multiple facts involved from human-computer interaction to course context. It points out the importance of new considerations that might appear during the application of new technologies or the replacement of old ones [4].

With the advancing development of artificial intelligence, regulation over the practical application of AI is bringing into our ethical concern. The ability and capability of AI come with increasing hazards when abused. In contrast to the inadequate resources and support of AI ethics, Brendel's team attempted to establish a start on ethical research applied to AI and raise more opportunities. They constructed a framework of ethical regulation that focused on decision-making, ethical concerns, and dimensions of perspective. This framework provides future scholars with a better approach to investigating the ethical behaviors of AI [22].

As shown above, researchers have analyzed and designed CAs from the perspectives of success and errors, domain knowledge, natural language processing, tasks, ethical concerns, and users. Current research confirms that personality is an important factor concerning CAs [23, 24, 25]. Some researchers explore the personalities of CAs [1]. Some research studies the framework from the perception of users by applying the OCEAN personality model (The Big Five) [24]. However, there is little research presenting the educational CA design about how we serve students with different personalities better to enhance technology accessibility and digital equity. Our work aims to bridge this gap by presenting an integrated high-fidelity educational CA prototype with four personality dimensions to meet users' needs by applying Hogan and Champagne's (1985) theory [8]. This work is among the first to design an educational CA with a user personality-based approach. We hope our design guidelines and examples will shed light on the fast development of educational CA design.

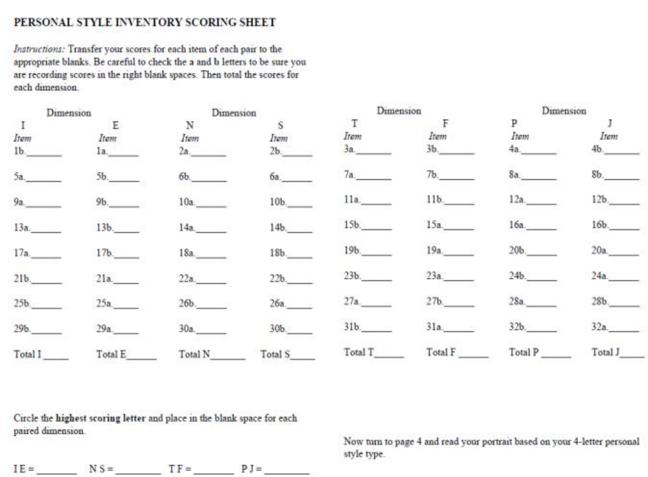
III. Method

A. The Personality-based Approach

Our previous study showed there were differences in the task accuracies of users with different personality dimensions when they interacted with a CA [26]. In this study, we designed the integrated high-fidelity prototype based on Hogan & Champagne's (1985) four pairs of personality dimensions: introversion VS extroversion (IE), intuition VS sensing (NS), thinking VS feeling (TF), and perceiving VS judging (PJ) [8].

We start with analyzing Hogan and Champagne's (1985) personalities and generating design guidelines for each personality style (see Table I) [8]. Based on the guidelines we constructed the logical modes of our CA. We designed two educational tasks to allocate our design logic and conversational flows. The research team of this work regularly meets twice a week, discussing and interpreting the descriptions of personalities according to Hogan and Champagne's (1985) theory and applies them to design [8]. We reach agreements to generate accurate design examples and guidelines. According to our previous studies, we used Juji as our design platform [26]. Due to the limitation of data retrieval ability of Juji, we designed one task about the tuition inquiry and the other one about requesting information for an on-campus student organization.

TABLE I. PERSONALITY DIMENSIONAL PAIRS



PERSONAL STYLE INVENTORY SCORING SHEET

Instructions: Transfer your scores for each item of each pair to the appropriate blanks. Be careful to check the a and b letters to be sure you are recording scores in the right blank spaces. Then total the scores for each dimension.

Dimension		Dimension		Dimension		Dimension	
I	E	N	S	T	F	P	J
Item	*Item*	*Item*	*Item*	*Item*	*Item*	*Item*	*Item*
1b.____	1a.____	2a.____	2b.____	3a.____	3b.____	4a.____	4b.____
5a.____	5b.____	6b.____	6a.____	7a.____	7b.____	8a.____	8b.____
9a.____	9b.____	10a.____	10b.____	11a.____	11b.____	12a.____	12b.____
13a.____	13b.____	14a.____	14b.____	15b.____	15a.____	16a.____	16b.____
17a.____	17b.____	18a.____	18b.____	19b.____	19a.____	20b.____	20a.____
21b.____	21a.____	22a.____	22b.____	23b.____	23a.____	24b.____	24a.____
25b.____	25a.____	26b.____	26a.____	27a.____	27b.____	28a.____	28b.____
29b.____	29a.____	30a.____	30b.____	31b.____	31a.____	32b.____	32a.____
Total I____	Total E____	Total N____	Total S____	Total T____	Total F____	Total P____	Total J____

Circle the **highest scoring letter** and place in the blank space for each paired dimension.

I E = ____ N S = ____ T F = ____ P J = ____

Now turn to page 4 and read your portrait based on your 4-letter personal style type.

B. The Integrated Prototype Design

Our integrated CA prototype was designed and constructed through an analysis of the descriptive keywords that appeared for each of the personality styles introduced in Hogan and Champagne's study [8]. Fig. 1 shows the integrated chatbot consisting of the I-E chatbot, I-S chatbot, F-T chatbot, and P-J chatbot, and the general-purpose chatbot for later comparison evaluation in future studies.

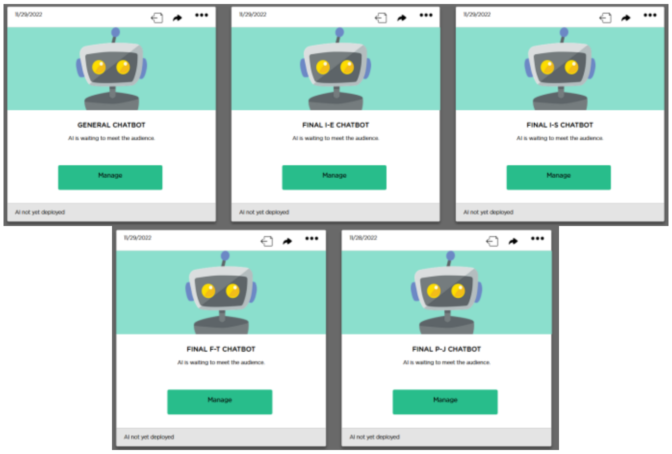


Fig. 1. Overall view of the integrated chatbot prototype.

IV. RESULTS

A. General Design Guidelines

From the description, we extracted the keywords, attributes, distinctive behaviors, and interaction expectations for each of the personality styles through a series of brainstorming and research group meetings. The final set of descriptions will be used to guide the design of CA logic and interaction modes to satisfy users' needs (see Table II). The descriptions of the personality styles have been carefully evaluated by the research team members via several research meetings and discussions. We classified the components of descriptions to be either applied to software, or inapplicable and need to be set aside. We then design accordingly focusing on users' personalities by following the descriptions in this study.

For introvert and extrovert users, we modify CA replies to users that match the conversation behaviors of these two personality types. For intuitive and sensing users, we regulate the information quantity and level of detail provided for each query when interacting with different types of personalities. For feeling and thinking users, the CA is designed to include more feeling and feedback from other people in replies for feeling users or to include more logic, reasoning, or facts in replies for thinking users. Finally, for perceiving and judging users, we let the CA provide fewer but stronger suggestions to perceiving users to reduce the space of hesitation and indecisiveness, which presents a problem for this type of personality. For judging people, choices are made effectively, and suggestions are provided after each question and answer to maximize query outcomes.

B. The Introversion vs. Extroversion Design

The descriptions extracted for the Dimension IE can be formulated into two sets of logical and interaction modes. Introverted people are less likely to be affected by non-subjective factors that exist in their environment, relationship, or background [8]. The reflection on our design of CA would be to display the final output with sufficient information and interact with less desire to urge for a specific choice. Introverted people are also reserved in socialization. Taking this into consideration, the CA needs to interact with users in a mild but polite way to prevent an intimate atmosphere during the conversation.

TABLE II. DESIGN GUIDELINES

Personality Dimensions	Description	Design Guidelines
Introversion – Extroversion	Introvert: "culture, people, or things around them. They are quiet, diligent at working alone, and socially reserved." Extrovert: "Extroverted persons are attuned to the culture, people, and things around them, endeavoring to make decisions congruent with demands and expectations."	Design guideline: the plain text is recommended. Design guidelines: may require more images and varieties.
Intuition-Sensing	Intuition: "The intuitive person prefers possibilities, theories, gestalts, the overall, invention, and the new and becomes bored with nitty-gritty details, the concrete and actual, and facts unrelated to concepts." Sensing: "The sensing type prefers the concrete, real, factual, structured, tangible here and now, becoming impatient with theory and the abstract, mistrusting intuition."	Design guideline: add organization description as "theory". Design guidelines: provide name, description, and events (as much information as possible).
Feeling-Thinking	Feeling: "As a consequence, feelers are more interested in people and feelings than in impersonal logic, analysis, and things, and in conciliation and harmony more than in being on top or achieving impersonal goals." Thinking: "As a result, the thinker is more interested in logic, analysis, and verifiable conclusions than in empathy, values, and personal warmth."	Design guidelines: provide participants/reviews feelings to arouse empathy. Provide member feedback together with information. Design guidelines: Use the if-else logic, and provide results that are more based on how the user can interact with the organization/ how college life will be like (analysis) based on different choices.
Perceiving-Judging	Perceiving: "The perceiver is a gatherer, always wanting to know more before deciding, holding off decisions and judgments." Judging: "The judger is decisive, firm, and sure, setting goals and sticking to them. The judger wants to close books, make decisions, and get on to the next project."	Design guidelines: We offer strong recommendations and help the user to successfully make final decisions. Design guidelines: we provide information instead of recommendations, and let users make decisions.

For example, the reply of CA to introverted users when answering cultural questions is designed to be polite and mild (see Fig. 2). After a user with an introvert attribute answers CA's question about interested culture, the user will receive a reply that explains the reason for this question with words that are polite and demonstrate mild emotion. Below is the reply after the user answers CA's question about the preferred culture in user the purpose of choosing a student organization. In this reply, we explain to the this question and express the will to maximize the user's experience in student organizations.

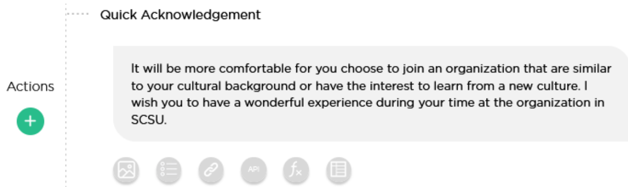


Fig. 2. Example of introvert I.

Another example where this similar feature was demonstrated was the reply to the last question to suggest student organizations (see Fig. 3). After students answered their preferred type of activities, the CA would explain the necessity of this question similar to the previous example. All other replies from CA to introverted users follow this pattern of controlling the level of intimacy with users.

Fig. 3. Example of introvert II.

Extrovert users are in the opposite status (see Fig. 4). They can easily adapt to their surroundings and can fit themselves during social contact [8]. The interaction mode of CA for such users should aim to create a passionate atmosphere that encourages close friendship. The conversation should be light, friendly, and information-rich. For example, the reply of CA to extrovert people is designed to demonstrate a closer friendship with the user. Replies to extrovert people will use words that express a closer relationship by including how the CA is asking this question to help the user have a better experience in the organization.

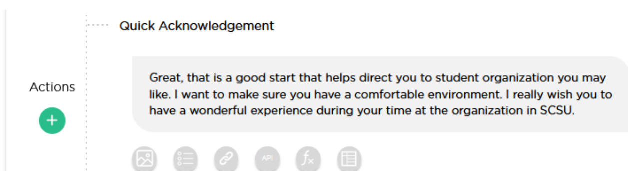


Fig. 4. Example of extrovert I.

Here is another example of a reply after the preferred activity question has been answered by the users (see Fig. 5). Student organizations may hold lots of different activities, and it may directly affect users' experiences in the organization. Therefore, whether the organization will hold the desired events that match user preferences or not is important and should be taken into consideration.

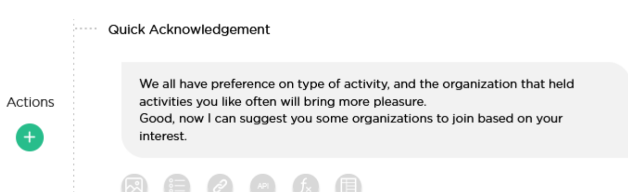


Fig. 5. Example of extrovert II.

The different replies based on personalities are to be triggered by user personality type, which is assigned by user input in personality check questions (see Fig. 6). In the Introvert-Extrovert prototype, the two possible values for personality types are introvert and extrovert. It will be used to guide the choice of CA replies in the guiding questions.

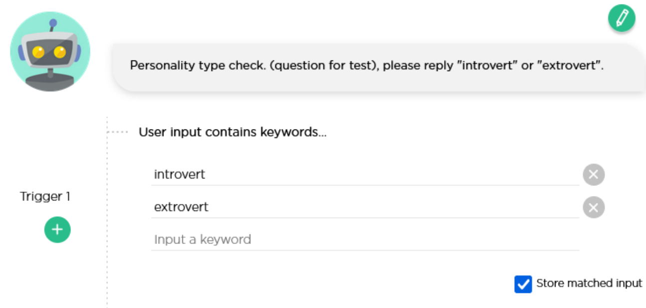


Fig. 6. Personality type selection.

After the user personality type attribute has been assigned, it will be used as one condition to trigger different chat flows that are designed with specialties for introverted people and extroverted people. Only one chat flow will be triggered at each time in each interaction (see Fig. 7).

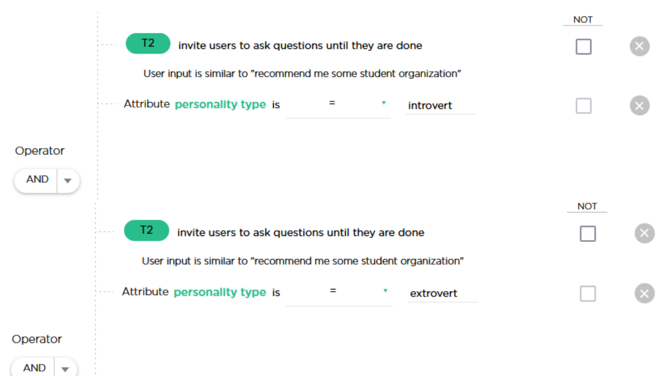


Fig. 7. Personality Conditions for introvert/extrovert.

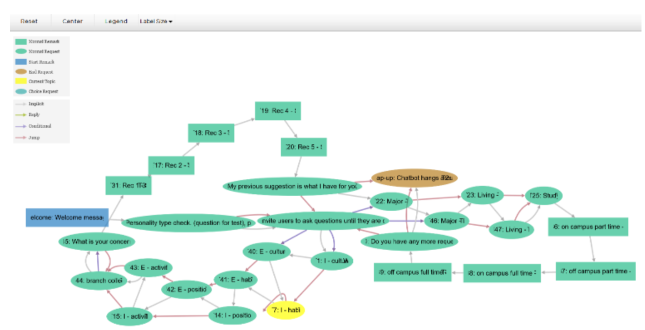


Fig. 8. Design logic of Introvert/extrovert.

Introverted and extroverted users will interact with the Final I-E chatbot. The general chat flow for both users will be similar with variations in reply. Starting with the welcome message, the CA will ask for the user personality type before the actual tasks begin so that different users can encounter different replies. Then the chat flow branches out based on the user's choice of tasks to perform. How the question will be asked by CA will be based on the user's personality type attribute initialized after the personality type check. After all questions have been asked, the system will display query results based on attributes collected from previous questions (see Fig. 8).

C. The Intuitive vs. Sensing Design

The description of the personality dimension of Intuition – Sensing primarily focuses on information preference. When applied to our CA, this preference will result in different reactions provided by users. Based on the personality description, we interpret that intuitive users demand the key information, concepts, or theories from messages delivered and are not interested in complicated details [8]. This is a clear expectation for CA's replies. For intuitive users, CA should provide straightforward information that directly answers the question or expresses the central idea. Miscellaneous details should be reduced respectively. For example, if this H/G club from the final results for the student organization query matches with preferences and attributes of the intuitive user after all questions are answered, the output will contain only the organization name, a short description, a link, and a picture (see Fig. 9). This result fits with descriptions of intuitive people. All key information is covered in the result with no other complicated details. Another example that follows the same design principles is the output of Campus Recreation (see Fig. 10). It contains the same kind of elements that target only the key information of this organization to provide the concrete idea of this suggestion. All other organization query results are subject to the same style.

This feature is also applicable to other query results. For example, the output for intuitive people in tuition check provides only the calculation result and a link to a webpage of detailed tuition composition. No other details are presented. The calculation may vary depending on attributes from the user applied after all questions are answered, but all outputs targeting intuitive users will follow the same style (see Fig. 11 and Fig. 12).

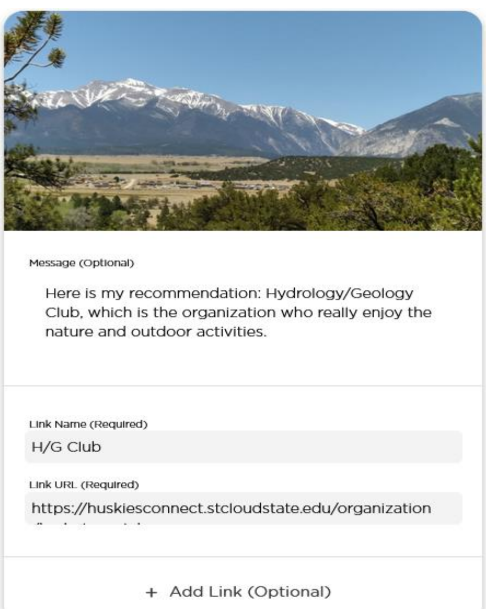


Fig. 9. Sample output-intuitive 1.

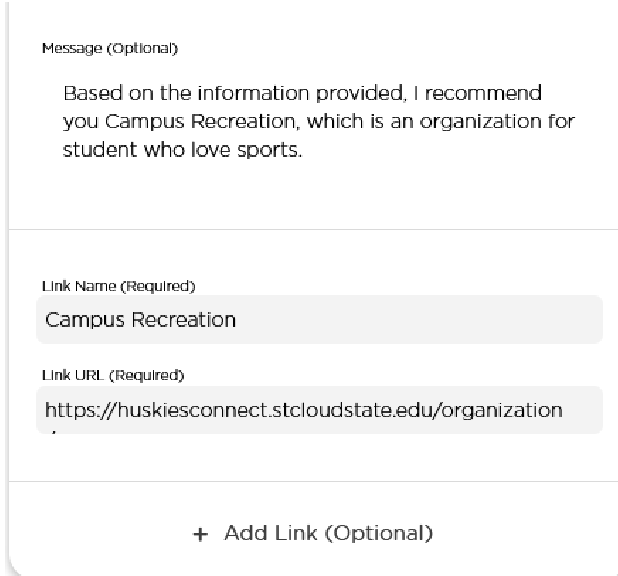


Fig. 10. Sample output-intuitive 2.

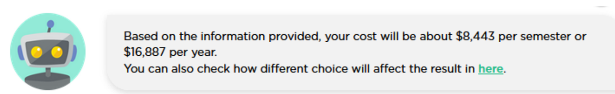


Fig. 11. Sample output-intuitive 3.1.

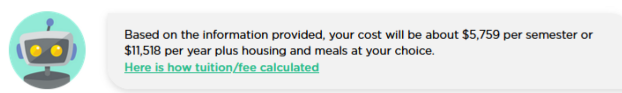


Fig. 12. Sample output-intuitive 3.2.

Sensing people need detailed information in contrast to intuitive people. They demand every piece of related information rather than abstractions that leave out something from the whole picture [8]. Replies to this kind of user for CA will need to provide full information that should not subjectively decide what the user may not need to know. Taking the example of the H/G club, the result of the student organization query for sensing users will contain much more information and more details compared to that of the intuitive output. Not only significant information should be covered, but also it should contain other supplementary information that can provide the user with a complete understanding of the organization in chat. This style of designed output fits with the preferences description of sensitive people (see Fig. 13).

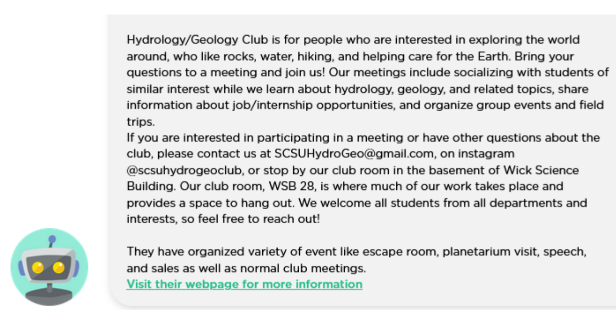


Fig. 13. Sample output-sensing 1.

Here is another example of detailed output for sensing people that subject to the same design principles. We take the output of campus recreation again for comparison purposes. This is much more detailed than the output of the same organization targeting intuitive people (see Fig. 14).

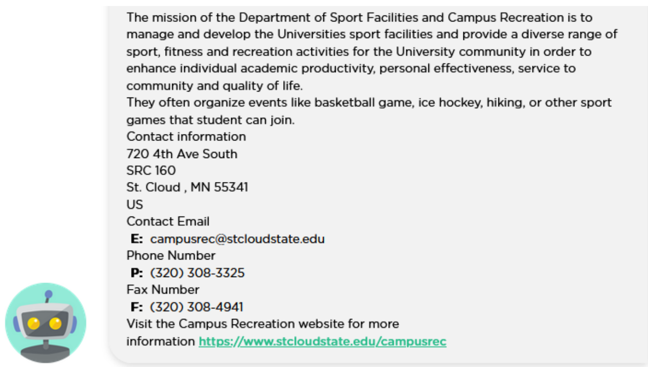


Fig. 14. Sample output-sensing 2.

When applying the same design principles to the tuition check query, we include the formula of the calculation into the output as supplementary information to increase user understanding of the result. Again, the calculation may vary depending on attributes from the user after all questions are answered. However, all outputs targeting sensing users will follow the same style (see Fig. 15 and Fig. 16).

The replies based on personality are to be triggered by user attributes assigned in personality check questions. In the Intuitive-Sensing prototype, the two possible values for personality types are intuitive and sensing. It will be used to guide the choice of CA replies in the final output. Guiding questions for both intuitive and sensing users are identical (see Fig. 17).

After the user personality type attribute has been assigned, it will be used as one of the conditions to trigger different outputs that are designed with specialties for intuitive people and sensing people. Only one output will be triggered at each time (see Fig. 18).

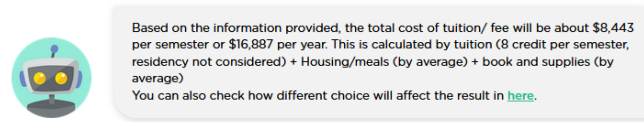


Fig. 15. Sample output-sensing 3.1.

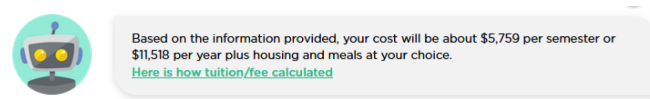


Fig. 16. Sample output-sensing 3.2.

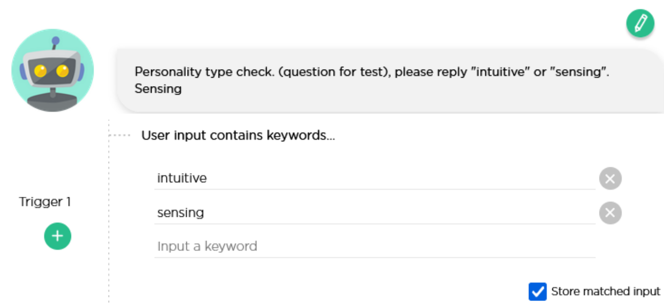


Fig. 17. Personality check for intuitive-sensing.

Intuitive and Sensing users will be interacting with the Final I-S Chatbot. Query results will depend on user attributes of personality styles that are assigned after the personality type check question. CA chat replies will be the same for both personality styles and vary only on the final output. Starting with welcome questions and personality checks, the user will need to select a task to perform. After the questions for either chat flow, the system will provide one output that matches user attributes collected from previous questions (see Fig. 19).

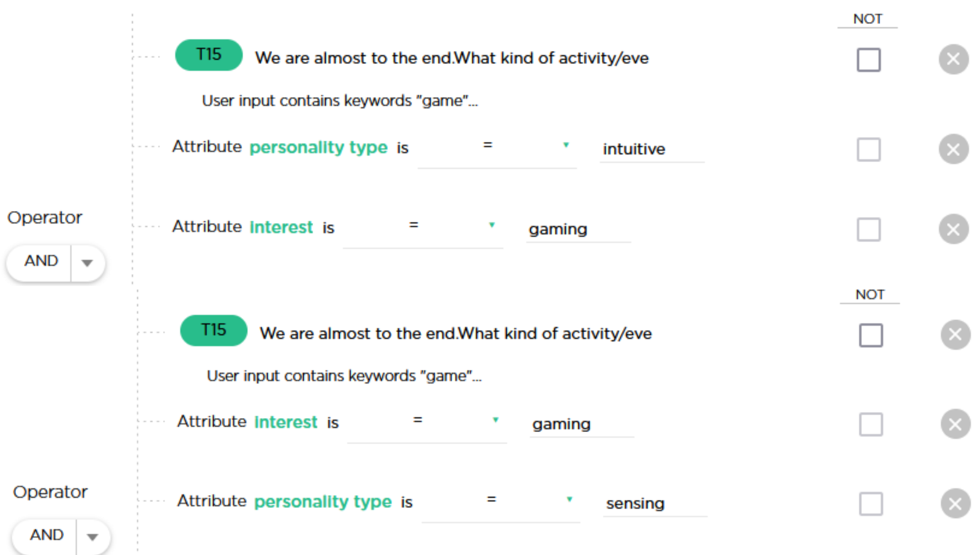


Fig. 18. Personality Conditions for intuitive/sensing.

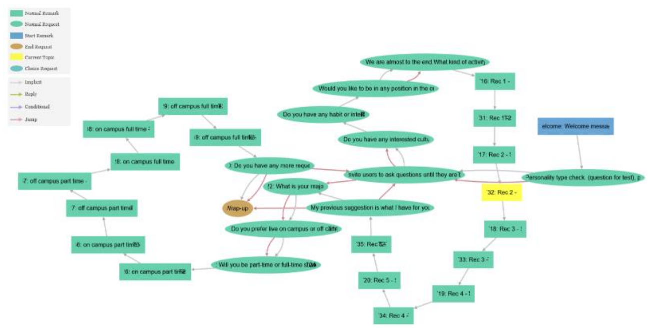


Fig. 19. Design logic of intuition-sensing.

D. *The Feeling-Thinking Design*

The description of Feeling-Thinking is not directly applicable as the previous two dimensions are. Feelers are more emotional and tend to favor humanistic reactions that address feelings. Thinkers on the opposite are more interested in logic-based suggestions [8]. When taking into consideration prototype design, CA would interact with perceptually feeling users and construct the reply to values more on emotions and feeling than logic and reasons. To think people, CA's replies must be supported by logic. The introduction of review and feedback from other people is necessary when interacting with feelers. And when interacting with thinkers, logic, and analysis weigh more than personal feelings.

This example demonstrates the replies based on feelings and reasons for the student organization recommendation (see Fig. 20). A suggestion that declares what experience would be more attractive to feelers. Therefore, replies to the feeler should include a description of what the experience will be like in the recommended organization.

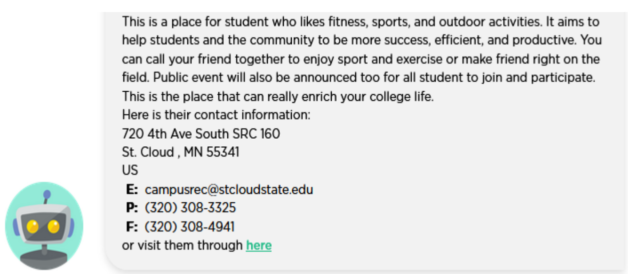


Fig. 20. Sample output-feeling.

However, thinkers would be more convinced by reasons why the organization meets their needs. In the description facing the thinkers, the functionality of the organization is introduced to demonstrate how might it fit with their preferences (see Fig. 21).

Taking another pair of organization query outputs as an example, we again worded the club description to focus on either experiences or functionalities (see Fig. 22). This feature is included in all student organization output.

As introduced in the previous two prototypes, the replies based on personality are to be triggered by user attributes assigned in personality check questions with 2 possible values — feeling and thinking. It will be used to guide the choice of CA reply in the final output. Guiding questions for both feelings and thinking users are identical (see Fig. 23).

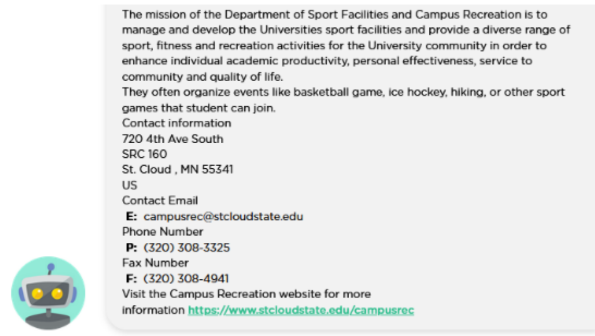


Fig. 21. Sample output-thinking.

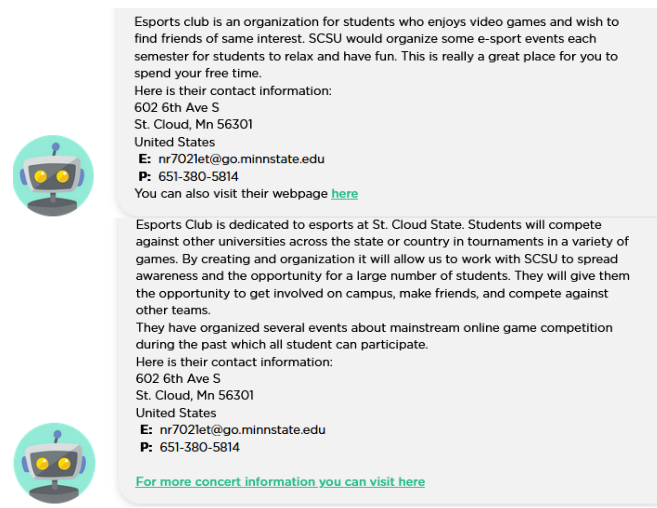


Fig. 22. Output comparison - feeling vs. thinking.

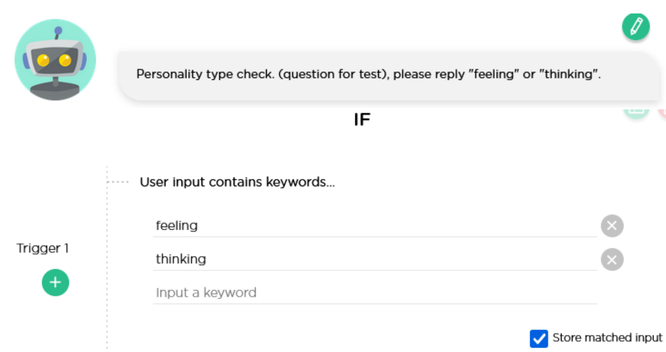


Fig. 23. Personality check for feeling-thinking.

After the user personality type attribute has been assigned, it will be used as one of the conditions to trigger different outputs that are designed with specialties for feeling people and thinking people. Only one output will be triggered at each time (see Fig. 24).

The prototype for Feeling-Thinking CA is embedded in the Final F-T Chatbot. The user will initialize the personality style attribute in the personality check question for CA to control the reply. The variation of this chat flow is primarily on the wording of query results. As users select tasks to be performed and answer the questions, the system will provide results that include descriptions that match with user preference tagged by their personality type. The flow chart resembles the one of Final I-S

Chatbot, but here the variation is based on information expression instead of information quantity (see Fig. 25).

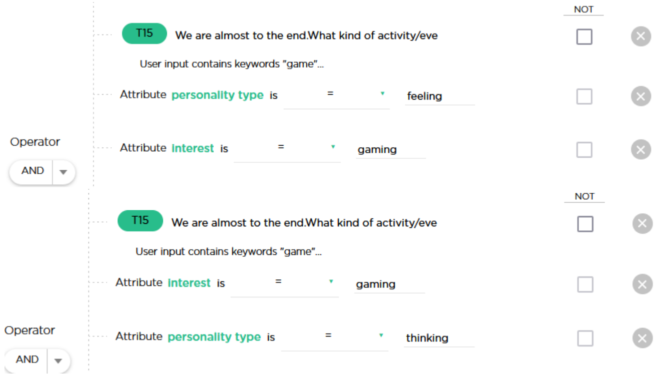


Fig. 24. Personality Conditions for feeling-thinking.

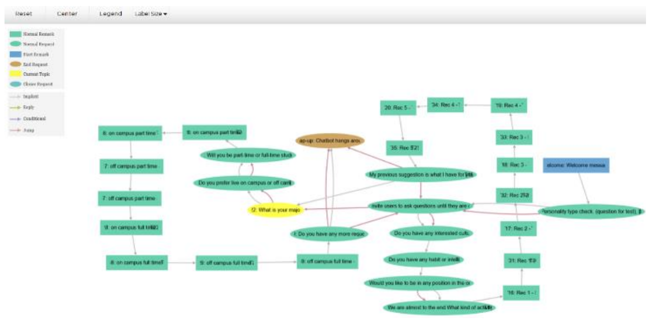


Fig. 25. Design logic of feeling-thinking.

E. The Perceiving-Judging Design

Perceivers by description are quite open to information from various perspectives and need to gather as much information as possible before making any decisions. They are cautious for each step. However, on the other hand, it can be hard for them to take the step and often become hesitant [8]. Our CA is addressing this issue by offering strong recommendations to push them to make decisions, or by restricting possible choices for perceiving users to limit the space for hesitation.

The perceiving people would require complete information as the sensing people do, but they may also encounter difficulties in making decisions and hesitation (). A reasonable solution would be to provide one suggestion with adequate information to prevent indecisiveness. Here is an example of output that contains the information of Esports Club (see Fig. 26). It contains descriptions and contact information. A link to the webpage is also provided for further interest.

Fig. 26. Sample output-perceiving 1.

Here is another example of organization output for perceivers containing the description and a link to the H/G club (see Fig. 27). These two examples, as well as other possible outputs for perceiving people, are embedded with the same level of detail as the output for sensing people. All the outputs for sensing users would also be appropriate for perceiving users due to the demand for detailed information mentioned in the descriptions for Perceivers.

Fig. 27. Sample output-perceiving 2.

Judgers will be the opposite of perceivers. They aren't as craving for complete information as perceivers, but they are good, determining decision-makers who seldom hesitate over the issue [8]. A CA needs to provide adequate information, as comprehensively as possible. It would be more appropriate to offer reasonable choices rather than streamlined options. An example to demonstrate the proper reaction to judging people would be providing multiple matched choices after each question is answered. This suggestion is provided by the system because the user declared an interest in Asian culture. Therefore, all matched organizations will be provided for this user to choose from (see Fig. 28).

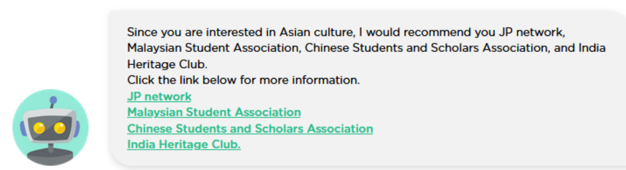


Fig. 28. Sample output-judging 1.

Here is another example of the outputs for judging people in the same question. In this case, user inputs demonstrate an interest in African culture. The outputs may vary depending on judging user input (see Fig. 29).

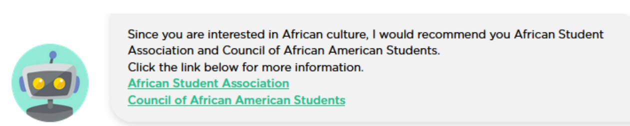


Fig. 29. Sample output-judging 2.

Such output is provided after each question is answered in the query. Here are other examples chosen from the outputs of another question for judging people (see Fig. 30). These responses will trigger when judging users demonstrate an interest in either gaming, hiking, or writing. Other responses will also be triggered through special keywords such as these examples as well.

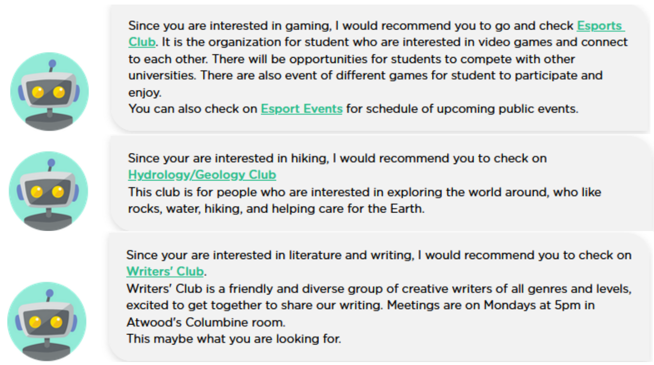


Fig. 30. Sample output-judging 3.

How chatbots reply to perceiving and judging users depends on user personality type attributes that are assigned through the answers to personality type check questions similar to the other three prototypes. The two possible values are perceiving and judging. The Chatbot will provide suggestions after each query question for judging users, or a single complete suggestion after all questions are done for perceiving users (see Fig. 31).

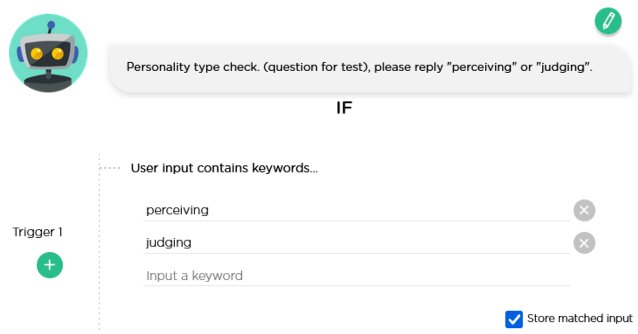


Fig. 31. Personality check for perceiving-judging.

For each of the questions asked, there is a reply waiting to be triggered if a user personality type attribute is judging. Here is an example of such a reply trigger after the question of user-interested culture. After user input has been stored as an attribute, it will be processed through verification for triggers (see Fig. 32).

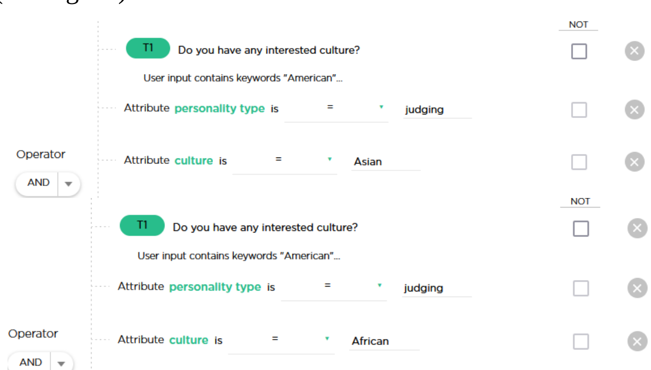


Fig. 32. Personality Conditions for perceiving-judging.

The difference between the chat flow of the two personality types is concentrating on the logic of demonstrating the query results. For a perceiving person, a strong recommendation of the best choice would significantly reduce space for hesitation and indecisiveness. For a judging person, a list of match results after each user attribute is assigned will be able to provide the user enough space to make decisions of one's own. After the start of the welcome message and personality type check, the user will choose tasks to be performed. A result will be triggered conditionally after each question based on whether the user is a judging person or not for the student organization task, and the final result will not be provided. In the tuition check task, the result will be displayed after the questions for both perceivers and judgers (see Fig. 33).

Fig. 33. Design logic of perceiving-judging.

V. Discussion

Our work provides design guidelines and examples to demonstrate how to design CAs based on a Hogan & Champagne (1980) personality approach [8]. We have designed an integrated prototype with four personality dimensions with different interactions with users with diverse personalities. However, there are challenges in the design process. For instance, even though the descriptions of the personalities in Hogan and Champagne's (1980) study were successful in transferring their concepts into understandable information [8], we have to further interpret the information when we transfer it into functional chatbots. The transition from personality description to features in the chatbot undergoes multiple stages of evaluation by the researchers. The original description must be separated into individual units that represent a possible feature that will appear in the final product. For example, here is part of the description for intuitive people:

"The intuitive person prefers possibilities, theories, gestalts, the overall, invention, and the new and becomes bored with nitty-gritty details, the concrete and actual, and facts unrelated to concepts" [8].

We interpreted this description and generated two sets of keywords. The first set of keywords suggests the preferred form or type of feedback and information received from the chatbot. The second set of keywords stands for the form and type of feedback to be avoided in chatbot responses for the intuitive personality. After identifying the component in this description, we have reviewed the extracted subject and re-evaluated it for the possibility of applying it to the actual product and the cost to do so. Not all the described characteristics are applicable to our design. The two sets of keywords will be applied to the prototype responses accordingly. We have to abandon those that don't fit with the design. Of the applicable features, some of them will be implemented into the design logically. We also need to adjust the original chat flow for almost all the personality prototypes to satisfy users' needs. We realized applying the same chat flow is not a proper solution. For example, perceivers are not as deceived as judgers and are relatively less efficient than judgers. There could also be different preferences on the level of detail in the responses received. The design of the chat flow for each personality is required to moderate the response and its level of detail. Such reflections on design are also applied to other personalities. Moreover, the platform we used to develop our prototypes also contains limitations. Juji is easy to use, yet sometimes too simple and not flexible enough to implement a design. We had to use an alternative solution to accomplish desired outcome. However, our work aims to present a detailed example to demonstrate how to design CAs with a personality-based approach by providing design examples and guidelines.

VI. Conclusion

With the fast development of chatbots, CAs are unavoidable to play an increasingly significant role in our education. Designing CAs based on students' personalities is crucial for education equity. This paper presented detailed guidelines and examples illustrating how to design chatbots with a personality-based approach. We hope this work will shed light on future CA design for education.

For future work, a comparison study will be conducted to evaluate the integrated personality-based design to the general design. Thirty college students with different personality styles will be recruited to evaluate this prototype and compare it to a general design. This study will use quantitative and qualitative methods to analyze the experiment data. This personality-based design and evaluation of CAs will bring a new focus to the user-centered AI design field.

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