Comparative Analysis of User Interaction: Evaluating Human Experience with UI Design against AI Integration in Meal Planning Applications

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In the field of Human-Computer Interaction (HCI), the integration of Artificial Intelligence (AI) into user interfaces has sparked significant interest and debate. The focus of this paper will be to present a comparative analysis of user interaction, focusing on evaluating Human Interaction.

Our project is centered around the different ways humans interact with artificial intelligence. Given the rapid advancements in AI technology and the limited research centered around it, it is essential that we learn how to best utilize it both in terms of ethics and efficiency. By delving deeper into this topic and conducting experiments, we aim to uncover valuable insights into optimizing human-AI interactions.

CCS Concepts: • **Computer systems organization** → **Embedded systems**; *Redundancy*; Robotics; • **Networks** → Network reliability.

Additional Key Words and Phrases: datasets, neural networks, gaze detection, text tagging

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1 INTRODUCTION

Artificial Intelligence programs have often been used in the form of chatbots to drive up user engagement. In video games, for example, the use of Natural Processing Language (NLP) to make intelligent NPCs that leave the player feeling a stronger sense of agency within the game, creating a more immersive experience [9]. On social media sites such as TikTok, AI algorithms create an almost addictive cycle that captures the user's attention for hours on end [13]. What we have noticed, however, is that the majority of these studies focus on the entertainment side of media.

Our project introduces a similar format that uses NLP, but this time we are looking away from entertainment and towards health [8]. We have created a meal-planning app that focuses on the user's current eating habits, dietary goals, and concerns to help create a weekly meal plan. The original part of this project uses a simple UI design where the user simply answers a series of questions and is presented with a variety of recipe options. The second part is where we have included a chatbot in place of the UI that will converse with the user to create the plan. We then tested this study on a variety of students to identify which style was easier to use and which provided better satisfaction.

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2 RELATED WORKS

Fortunately, there are a series of studies that have taken a look into how users are engaged with chatbots, so before our study began, we had an idea on what to look into for our own. One study included a group of 54 undergraduate students who were asked to complete a series of tasks only using Slack and different levels of search bots to communicate and perform searches as a way to better understand the bot is able to affect collaborative efforts [2].

Jayati Dev and L Jean Camp, for example, take on a psychological lens when discussing the effects chatbots have had on users. In a study where they monitored 30 one-to-one conversations between a user and a chatbot, they found four specific interactions that users ended looking for in the bot: 1) A place to discuss emotions and feelings, 2) Seeking help and personal advice, 3) Venting about personal opinions, and 4) Trying to learn more about the chatbot [5]. We were most interested in the second one where it seemed that users are inclined to give chatbots their background before anticipating the program to provide judgment on what they should do [5]. This works well for our study since the end goal of our chatbot is to help users reach their dietary goals. That being said, the fourth one is also helpful as it provided insight on what we needed to include with our chatbot — more things to discuss such as a name and a purpose outside of "meal planner".

Another important reference included an smoking intervention app that had a purchasable "pro" version that included a chatbot to help with smokers' quit success rates [17]. The end result showed statistically significant evidence in favor of the chatbot. This study should be taken with a grain of salt, however, as it had some confounding variables that have not been properly looked at, but in the case of this paper, we are more concerned with how the data was collected. The success rate was decided based on how often the users logged into the app and their self-reported abstinence level which was collected monthly [17]. This introduces a limitation for our research as we did not have as much time to look into the long term impact of the meal-planner.

Moving on to meal planning, it is cited in the latest version of Canada's Dietary Guidelines as one of four important food skills that help individuals choose, purchase, and prepare healthy snacks and foods on a regular basis for themselves and members of their household [8]. Meal planning can be an extraordinarily useful tool to boost physical and mental health, even contributing higher levels physical activity [3]. There is also the added benefit that planning one's meals ahead of time is greatly able to reduce the amount of food waste within households [19] Having the right foods in the right amounts is of paramount importance to maintaining a healthy lifestyle, and this can backed up through how much nutritional medicine is use psychiatry [18].

Firstly, a researcher by the name of Matteo Briguglio took a deep look into eating and its diverse connections to mental health [3]. He found out that there is a bidirectional relationship between healthy eating and superior mental health in adolescences. In addition to this, more studies have found that a healthy diet can drastically help psychiatric disorders, and can potentially be an even better fix than traditional solutions [18]. With these incredible results, it also makes sense that eating healthy would overall increase the happiness of somebody. That is exactly what was researched by Veenhoven [20]. Through his studies of 27 different countries, he found that there is a strong linkage between healthy eating and overall happiness. The psychological benefits of eating a balanced diet are incredible, and the physical implications are no less significant. Reducing diseases such as obesity, heart disease, and diabetes, healthy eating can dramatically help increase life spans [15].

These varying factors make healthy eating/dieting incredibly beneficial, and the easiest way to diet is to have a meal plan [14]. In our research, we found that J M Brunstrom wrote an article researching why meal planning is so effective at achieving dieting, and he concludes that it helps control meal sizes [12]. Meal plans can achieve all the desired nutritional needs based on the body type of a person; but, how does it do it?

When creating the application, we needed the make sure the calculations were perfect to get optimal results. For the calculations, we needed a very important data point, the basic metabolic rate of the user. In order to get that, we first need Resting Energy Expenditure (REE). There are two main formulas used to attain this; the Harris Benedict Formula and Mifflin-ST Jeor Formula. In a paper breaking down the two [1], it was found that both are reliable. Based on this, we decided to go with the Mifflin-ST Jeor formula, because of the formula's simplicity. We then had to extract some values of the user that are necessary: age, height, weight (current and desired), sex, activity level, and body type. These different inputs allow us to use the formula to create a close estimation of needed calories and macro nutrients for any person.

3 METHODOLOGY

To begin, we have two separate versions of the prototype. In the first version, the UI takes in a series of variables inputted by the user. After the user clicks continue, they will move onto the next page where a series of meals will appear. Due to the simplicity of the design, we expect that the UI will take far less time to complete than the second version which involves the chatbot.

The is a big restriction to look at from this version of the prototype. It prioritizes the user's health on their behalf. While many people who attempt meal planning do it for the sake of bettering their health, it is not the only reason that exists [14]. Meal planning is a strategy often used by people with busy schedules and a low income as a way to cook up cost-efficient, easy to prepare dishes for themselves or their families [10].

As we can see from the figure below, there is not much instruction for the user to follow. As it involves extra typing and having a more specific conversation, it would not end up being as easy to fill out as the UI version. It would be unusual, then, for it to take up more time. That being said, research has found that consumers often show higher levels of engagement when provided with more interactive features. And because users are often more likely to seek help and personal advice from tools they can chat to, we believe that this second version will be far more effective in providing user satisfaction [5].

Fig. 1. The current version of the prototype, both UI (top image) and NLP chatbot (bottom image)

3.1 Participants

The participants of this study were 12 volunteers, mainly consisting of college students at Colorado State University around the ages of 18-21. College students are a particularly interesting demographic as they vary greatly in dietary needs [11]. While some of the subjects are more health conscious and are only interested in searching for a balance diet, others gravitated towards quick and easy meals that can fixed up around demanding schedules. As a result, they will be able to provide a good foundation for how users can interact differently between the UI prototype and the chatbot.

3.2 Experiment Design

The 12 users were each asked to perform both programs. To avoid biases, the order of which program the participant interacted with first was switched with each one. All individuals were instructed to be honest with their inputs and to create at least two separate plans.

For the sake of the experiment, the users were specifically asked to input the exact same information to the chatbot that they submitted to the interface. This includes their age, height, weight, gender, activity level, desired weight, and any dietary restrictions they had. By controlling for the information being sent in to both versions of the prototype, any changes in user satisfaction and engagement could be directly attributed to the method of interaction between the program and the participant.

The effectiveness was measured two ways. To begin, the subject was timed for each task to determine how easy it was to navigate the prototype. The second method of data collection involved a survey at the end where the user could determine their personal satisfaction with the program and how likely they were to stick to the meal plan that they made. This survey specifically asked the participant to rate their level of engagement. With all the collected data, we were able to go through the results to determine whether the chatbot feature helped or hindered the overall experience of the meal planner.

4 RESULTS

Once the participants had all finished their tests, their data had been compiled into a spreadsheet. This is where their average speed, engagement, and satisfaction for each program had been calculated. Our initial null hypothesis was that there would be no difference between the UI program and the NLP. As the goal of the experiment is to see if the method of how participants interacted with the program had an effect on their personal engagement and satisfaction.

It appears that some users were not interested in engaging with the program, causing the dip near the middle of the data. This may cause some of our results for the Natural Language Processing portion to be dragged downwards, but it does offer up some interesting points for the discussion. For now, we will show the results of the prototype.

4.1 Time

As suspected, the time to complete the NLP version of the program is far longer for most subjects than the time to complete the UI version. (Figure 2) shows the data in the form of a chart. The grey line depicting the times for NLP is consistently higher than the blue line representing UI.

The average time the participants took to complete the UI version of the prototype was around 167.33 seconds, which is 2 minutes and 47 seconds. This average for the NLP version that only included the chatbot was up to 351.17 seconds, or 5 minutes and 51 seconds. Even including the outliers, this is a large jump in time and it implies that the participants were spending more time with the program when it involved the chatting feature.

This is an interesting discovery due to the fact that participants were specifically asked to only provide a certain set of information. We did notice, however, that the majority of students ended up taking the time to actually chat with the chatbot. For example, they would ask for the bot's name before getting more information on meal planning. With this added chat feature, we could already see users having a higher level of interaction with the program. The next two variables that discuss the user's engagement and satisfaction will follow a similar pattern.

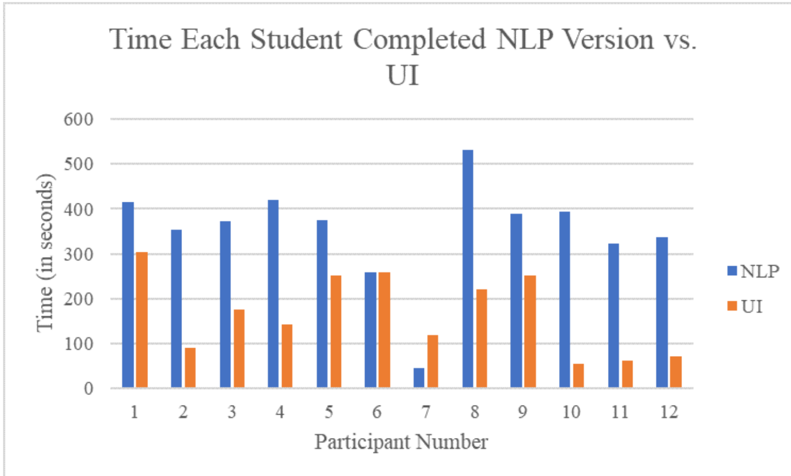

Fig. 2. The time each participant took for the UI and the NLP.

4.2 Engagement and Satisfaction

Even more important to look at than the times, this data also reveals that the NLP program provided more engagement and satisfaction than its alternative. Tables 1 and 2 look into the ratings that each participant gave themselves. Let's look at the satisfaction ratings first.

Participant Number	UI	NLP
1	5	6
2	5	7
3	5	7
4	5	7
5	5	6
6	4	4
7	4	2
8	5	8
9	7	8
10	2	5
11	2	7
12	3	7

Table 1. Satisfaction rates of UI against the NLP

From this data we can determine that the average level of satisfaction from the UI was around 4.5 with a standard deviation of 1.39. Compare this to the average satisfaction of the NLP, 7, and its standard deviation 1.87. This is quite a significant difference to consider. Our participants have reported the chatbot provided more satisfaction than the classic user interface. Because the same information was inputted into both versions of the program, we can determine that the simple action of talking to a chatbot is what is resulting in this change.

Participant Number	UI	NLP
1	5	6
2	4	7
3	5	7
4	6	8
5	5	8
6	5	7
7	4	5
8	5	5
9	7	6
10	5	8
11	5	6
12	5	7

Table 2. Engagement levels of UI against the NLP

A similar story can be told from Table 2 which is focused on the engagement levels of each user. The UI section ends with a mean of 5 and a standard deviation of 0.95. Just like with the previous table, NLP comes out on top with an average and standard deviation of 7.5 and 1.56 respectively. Another thing to note is that for both versions of the prototype, engagement levels have far less variation than satisfaction. Therefore, we can conclude that the participants are more in agreement in that the chatting feature is far more engaging than the UI.

All of this data paints an interesting picture about how the users are interacting differently with the interface. Now that we have looked into the numbers, let's discuss what they mean.

5 DISCUSSION

Overall, we've noticed that the chatbot feature resulted in higher user engagement and satisfaction when making a meal plan. This could be for various reasons. For starters, we know already that people who use chatbots gravitate towards asking for advice and wanting assistance with problems that they are having [5]. It is not surprising, therefore, to find that nutrition is a heavily studied topic in the growing AI industry [4]. Simple surveys and UI programs are handy, but with a topic as prevalent and sensitive as what we eat, the personal conversation that chatbots bring can make all the difference.

We know that meal planning in particular has a significant benefit in a person's life. For example, a system in Ghana, has taken the time and resources to create a nutritional, locally-sourced meal-planning package to provide to their schools [7]. This is no small feat, and the final conclusion of that study encourages other countries to do the same. Unfortunately, a simple UI program that only takes in certain inputs may not provide the same depth as a nutrition specialist, but those are not so easily accessible. Although an NLP program does not have the same expertise as a specialist, however, it is still able to maintain the necessary details to make a meal plan while creating a much friendlier environment [6]. This is evident in our results.

5.1 Limitations

The limitations of this study begin with the small time frame. Four months to create the prototype and perform the study has led to areas that were rushed. One of the biggest consequences is the sample. All participants involved in this test were college students at Colorado State University. This is a very specific demographic that cannot be used to make many large generalizations.

Another small limitation to consider was the data collected. Looking back, it would have been best to record the chat conversations each participant had with the NLP version of the prototype [6]. This would have helped find more nuances with how the users were engaging with the program [16]. By the end of the study, unfortunately, the majority of the data was purely quantitative, leaving little room for understanding how students interacted with the chatting feature.

6 CONCLUSION

There are a great deal of benefits that come from meal planning, from saving money to reducing food waste around the house. The nutritional benefits are what we have decide to look into with our meal planning program. More specifically, we wanted to look into whether or not the inclusion of a chatbot within a meal planning program would increase a user's satisfaction.

The prototype contains a simple user interface in which the user would input their data (height, weight, etc.) to then receive a personalized meal that fit their needs. The second version included the chatbot for the user to interact with. In the end, we found that the majority of our users found a significant amount of satisfaction from the chatbot, taking more time to interact with it, and claiming that they were more likely to follow along with the meal plan created out of that version. From this test, we can conclude that a chatbot has the ability to grant users higher levels of satisfaction when discussing their meal plans.

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