A Multi-Party Conversation-Based Effective Robotic Navigation System for Futuristic Vehicle

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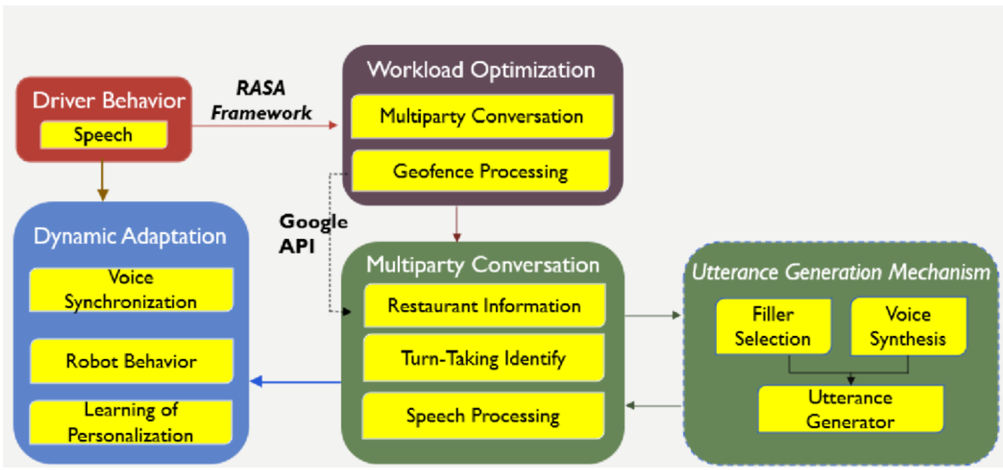

Abstract

In response to the growing need for advanced in-car navigation systems that prioritize user experience and aim to reduce driver cognitive workload, this study addresses the research question of how to enhance the interaction between drivers and navigation systems. The focus is on minimizing distraction while providing personalized and geographically relevant information. The research introduces an innovative in-car robotic navigation system comprising three subsystem models: geofencing, personalization, and conversation. The dynamic geofencing model acquires geographic details related to the user's current location and provides information about required destinations. The personalization model tailors suggestions based on user preferences, while the conversation model, employing two virtual robots, fosters interactive multiparty conversations aligned with the driver's interests. The study's scope is specifically confined to interactive conversations centered on nearby restaurants and the driver's dietary preferences. Evaluation of the system indicates a notable prevalence of neutral expressions among participants during interaction, suggesting that the implemented system successfully mitigates cognitive workload. Participants in the experiments express higher usability and interactivity levels, as evidenced by feedback collected at the study's conclusion, affirming the system's effectiveness in enhancing the user experience while maintaining a driver-friendly environment.

Keywords: Human-Robot Interaction, Multiparty Conversation, In-Car Navigation

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1. Introduction

In the rapidly evolving landscape of automobile technology, substantial strides have been made to enhance the efficiency and usability of vehicles. However, the in-car navigation experience for drivers has not witnessed a commensurate improvement despite the proliferation of innovations (Voros et al., 2022; Voros et al., 2019). The prevalent use of in-car navigation systems, reliant on the Global Positioning System (GPS), underscores the need for a more user-friendly and interactive approach (Alkutbi et al., 2019).

Despite the increasing reliance on in-car navigation systems, user experience and interaction have not kept pace with technological advancements. This discrepancy can be addressed by leveraging the principles of social robotics, particularly those associated with multiparty conversations-based robots (Karatas et al., 2015). The present surge in in-car navigation system usage, predicted to reach a 56.91 billion market value by 2030, necessitates a reevaluation of user experience (Automotive Navigation Systems Industry Forecast, 2021-2030).

Driver distraction, accounting for a significant percentage of vehicle accidents, underscores the importance of refining the in-car navigation interaction model. The conventional approach of manually inputting destinations and monitoring routes on flashy displays contributes to an artificial atmosphere and heightened distraction (Grahn & Kujala, 2020; Braun et al., 2019). A personalized model for frequent operations could alleviate distraction and enhance overall user experience (Yi et al., 2020).

Moreover, the integration of natural-like conversations between users and navigation systems, enabled by multiparty conversation systems, can significantly reduce cognitive workload and foster a more friendly atmosphere (Lin et al., 2018; Samal et al., 2020). Social robotic techniques, proven effective in diverse fields, can be optimized to enhance the efficiency of navigation systems, ensuring socially acceptable and engaging interactions (Zepf et al., 2020; Yared & Patterson, 2020).

Notably, social robots have demonstrated success in assisting differently-abled individuals, showcasing their potential to enhance navigation system efficiency (Lin et al., 2018). For instance, the "NAO" robot effectively taught children with autism, emphasizing the adaptability of social robotic techniques (Lin et al., 2018). The concept of an "active" navigation system, as opposed to a "passive" one, has shown promise in improving engagement and reducing cognitive workload, especially in the presence of familiar individuals (Rea et al., 2020).

Research conducted in Japan on the Navigational Multiparty based Intelligent Driving Agents (NAMIDA) system indicates that a multiparty-enabled driving agent reduces driver workload and enhances the overall driving experience (Karatas et al., 2015). Similarly, MAWARI, another application of social robotics, employs multiparty conversations to create a more comfortable environment for users, reducing cognitive workload during discussions (Bertel & Rasmussen, 2014; Ham et al., 2011; Arkowski, 2019).

While dynamic geofencing is a concept integrated into some modern in-car navigation systems, its potential synergy with personalization, multiparty conversation, and social robotics remains largely unexplored. Future research should delve into the possibilities of combining these concepts to elevate the usability, efficiency, and accuracy of in-car navigation systems, particularly for futuristic vehicles (Zepf et al., 2020).

This research aims to implement a system with two robots engaging in multiparty conversations to suggest nearby restaurants to the driver. The incorporation of dynamic geofencing ensures comprehensive information about the surrounding environment. The personalized model aims to provide a unique and tailored experience, moving away from the artificial atmosphere associated with traditional navigation systems.

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2. Methodology

Implemented in-car navigation system consists of a personalization model, geofencing model conversation model, and the system interface. Python is used as the main programming language of system development. All the models are synchronized with the robot interface.

2.1. Geofencing Model

Having a virtual perimeter on a real-world geographic area can be described as a geo-fence. Geofence can be static or dynamic. Static geo-fence is not changed based on any factor such as users' location and it can be either a circle or any other polygon in shape whereas dynamic geofence can be changed by factors such as users' location and it can be only circular. The Geofencing model of the implemented in-car navigation system is used to obtain the details about the current location of the user and find the restaurants with a geofence within a 5 km radius. To fulfill this requirement, google maps geolocation Application Programming Interface (API) and google maps places API were used. Geolocation API returns the longitude and latitude of the device with the help of nearby cell towers and Wi-Fi nodes. Google Maps place API is used to obtain the restaurants within a 5 km radius based on the user's location that is obtained by the geolocation API.

The above-described geofencing model had to be modified to integrate with the implemented system due to the lack of restaurant-specific details obtained from google maps places API. In other words, google maps places API does not send the details about either restaurant type (such as Arabic, Indian, Sri Lankan, or Italian) or restaurant budget range. Even though there is a budget scale in the 1-5 range, most Sri Lankan restaurants do not have the budget rating filled. So, they were obtained as nil. To overcome this phenomenon, it is used a sample dataset that has different types of restaurants with different budget margins. So that the location obtained from geolocation API is fed into the filtration method of the dataset to obtain possible nearby restaurants to suggest to the user. After the users' requirements of the type and budget are obtained by the interactive conversations, there are fed into the filtration method to select a restaurant based on the users' preference.

2.2. Personalization Model

The personalization model is used to provide the user with more personalized suggestions on restaurants. Despite it examining the possibilities of adapting machine learning concepts such as unsupervised learning and reinforcement learning to implement the personalization model, those concepts seem to be not fully adaptable to the personalization model due to the nature of the rapid expansion of the dataset based on the geofence. In other words, when the geofence changes, there will be a new set of restaurants fetched into the database and these fetched restaurants do have not got required information such as budget level and restaurant type by default. As a solution to the above-discussed scenario, it used a table to implement the personalization model which stores the users previously selected restaurants, and it is coupled with the filtration method where the filtration method selects the restaurant with the highest previous selection count among all possible restaurants based on the user's preference. If the user selects the same restaurant again, it immediately updates the data table by increasing the previous selection count by 1 whereas if the user selects a restaurant that has not been previously selected by the user, it immediately updates the previous section count value from 0 to 1. The main advantage of this model is the ability to integrate with the conversation model and geofencing model without affecting the desired workflow of those models. Despite the simple nature of the personalization model, it has been able to handle rapidly changing datasets based on geofence more effectively.

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2.3. Conversation Model

In the development of a Multi-Party Conversation-Based Effective Robotic Navigation System for Futuristic Vehicles, the RASA framework is instrumental in facilitating communication between the robots and the user, employing natural language processing and machine learning components. The utilization of RASA framework can be delineated through various stages:

2.3.1 Implementation of RASA Components:

1. RASA NLU - This component is deployed for intent classification, playing a pivotal role in understanding user inputs. In the context of the navigation system, intents may include commands related to route guidance, destination preferences, or specific instructions. Intent examples, such as "Navigate to [location]" or "Find [restaurant type] nearby," are utilized as training data to enhance the NLU model's understanding of user intent.
2. RASA Core - As the machine learning-based dialog management tool, RASA Core processes structured inputs from RASA NLU and predicts the next best action using LSTM neural networks. Reinforcement learning is employed to iteratively improve action prediction. In the navigation system, this could involve predicting the appropriate response to user queries or requests, such as suggesting routes, providing information about nearby points of interest, or engaging in multiparty conversations.

2.3.2 Conversation Model Development Steps:

1. Generation of NLU data - The first step involves creating training data for RASA NLU. Intents related to navigation and user preferences are defined, accompanied by examples to train the Natural Language Understanding model. For instance, intents like "Navigate," "FindRestaurant," or "SetPreferences" could be established.Generation of responses - In this process, it has to be defined what type of responses the user gets when the model detects a specific intent.
2. Generation of Responses - Defining responses for specific intents, such as providing navigation instructions or suggesting points of interest, is a crucial step. This ensures that the robotic system can appropriately respond to user inputs.
3. Generation of Form Data - While form data is typically used for collecting specific information, in the navigation system, it might not be directly applicable due to the variability in expressing preferences. Instead, preferences are treated as intents, allowing for more flexibility in user interactions.
4. Generation of Story Related Data - Stories are crafted to train the model on sequences of user intents and desired responses, allowing the system to handle different conversation flows. Stories are generated based on user intents, such as requesting navigation to a specific destination or expressing preferences for types of restaurants.
5. Generation of Rules - Rules are defined to ensure specific parts of the conversation follow predefined paths. For instance, rules could dictate how the system responds when a user expresses a clear navigation command or preferences for a restaurant type.

2.3.3 Integration with Speech and Text Modules:

The conversation model is seamlessly integrated with speech-to-text and text-to-speech modules. This integration allows the robotic system to convert its responses into spoken language and interpret user instructions provided in speech form.

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2.3.4 Personalization through Voices:

The system is personalized by assigning two distinct voices to the robots – one representing a male robot and the other a female robot. This adds a layer of human-like interaction and enhances the overall user experience.

In summary, the RASA framework is a key enabler in the development of a Multi-Party Conversation-Based Effective Robotic Navigation System for Futuristic Vehicles. It empowers the system to comprehend user intents, predict appropriate actions, and engage in dynamic, effective conversations, making the futuristic navigation experience more interactive and user-friendly.

2.4. Robot Interface Design

With the consideration of futuristic vehicle designs focusing on interior designs, it is identified that the system should be implemented as a virtual system that works with any display device. It is also observed that virtual social robots tend to get higher attraction due to the range of possible animations (Polishuk P & Verner I M, 2012). The robot interface is implemented to have a common platform to interact with the user and the navigation system. The personalization model, conversation model, and geofencing model are synchronized with the interface.

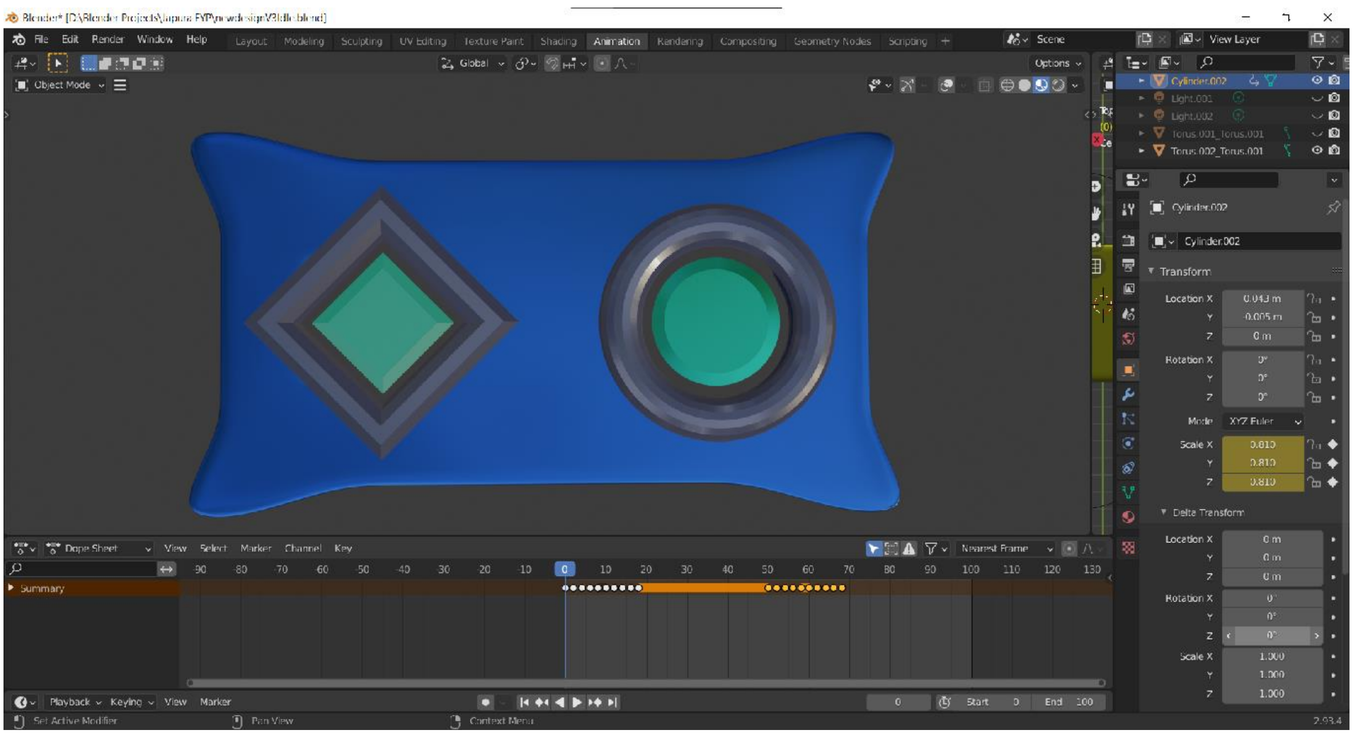

Figure 1: Design in blender

Animations of the robots are designed using blender software which is an open-source 3D creation suite. Blender is a cross-platform application and supports the entirety of the 3D pipeline (About — blender.org, n.d.). Considering the basic design, it is used 2 different shapes to represent 2 robots where one robot is represented by a diamond-shaped design, and the other robot is designed using a circular shape. Four animations were mainly used to represent different states of the system;

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1. Both robots are in idle - As in Figure 2, this represents the state where both robots are neither listening nor speaking. This is the initial state of the system. This was represented by animating two shapes of the robots to move in the opposite direction while scaling up.
2. The left robot speaks while the right robot listens - The robot design depicted in Figure 3 represents the scenario of the robot shaped like a diamond speaking while both the robot shaped as a circular and the driver listen. It is represented by the animation where the diamond-shaped robot scales up and scales down recursively while the circular-shaped robot remains still.

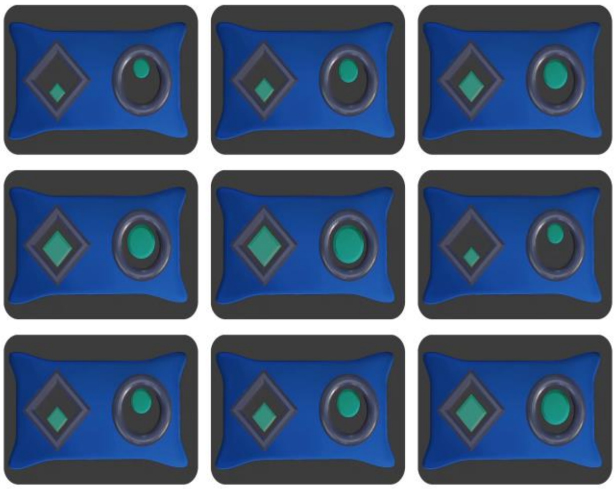

Figure 2: Sequences of idle animation

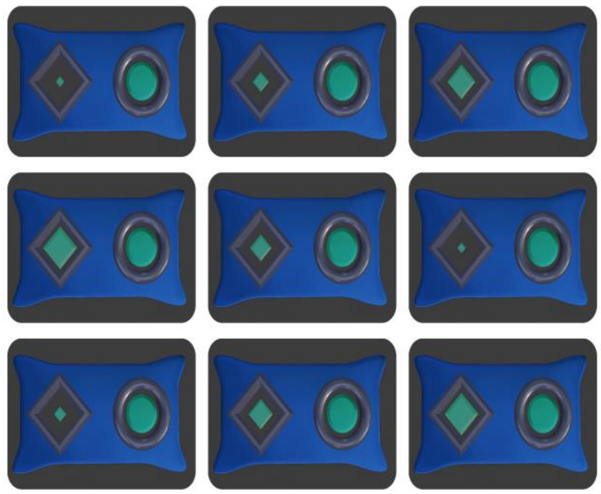

Figure 3: Sequences of left robot speaks animation

3. The left robot listens while the right robot speaks - Figure 4 represents the scenario of the robot shaped as a circular speaks while both the robot shaped like a diamond and the driver listens. It is represented by the animation where the circular-shaped robot scales up and scales down recursively while the diamond-shaped robot remains still.

4. Both robots listen - Figure 3 illustrates the scenario where the user speaks. This was represented by both the robots scaled up and down in a similar manner recursively.

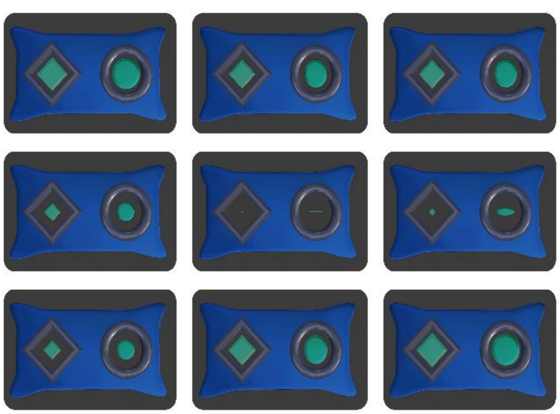

Figure 4: Sequences of right robot speaks animation

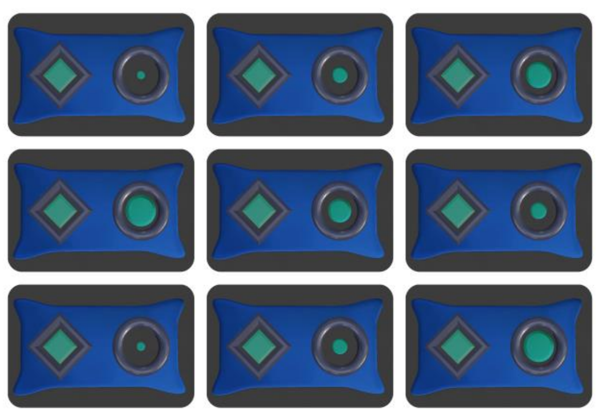

Figure 5: Sequences of both robots listen animation

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Above mentioned animations were converted to MP4 file format with a 10-second duration and added to the interface design python script to synchronize with desired actions.

3. Experiment

The opportunity was given to 15 candidates above 18 years of age who use navigation systems frequently to have a conversation with the in-car navigation system according to their preference of restaurant selection. Before the experiment, the candidates were asked to search nearby restaurants from their mobile phones according to their preference of budget level and restaurant type. After they were done with the restaurant search process the experiment started. The implemented navigation system was set up on the laptop and placed on a table in a room where there was less noise compared to outdoor. The main reason behind the selection of a quiet room to experiment is to minimize the effect of external noises on the conversation. Before the experiment, they were given a short introduction to the implemented system and the multiparty conversation approach. Furthermore, they were given an idea about the budget levels and types of restaurants.

3.1 Obtaining the number of speech misdetection

The number of occurrences where the user's speech has been detected incorrectly was obtained. This was used as a measurement obtained internally to measure the accuracy of the developed conversational model. To obtain this count, a variable was used that increases its' count whenever the system detects a speech misdetection which leads to asking the user to repeat what he/she said earlier.

3.2 Obtaining and analyzing the emotions of the user

As an evaluation mechanism, a loosely coupled emotion detection process was used with the implemented system to capture the emotion of the user within every 5 seconds of the interaction period. Counts of each emotion such as happiness, anger, and sadness which are detected during the session are used as an evaluation mechanism of the users' interaction with the system.

3.3 Obtaining the user feedback

User feedback was used as a measurement to identify the ability of the system to enhance the user experience and interaction. User feedback was obtained through questionnaire which were given at the end of the experiment. There were 14 questions in the questionnaire regarding different capabilities of the system where the user can express the usability and interactivity of those capabilities based on his/her point of view. The questionnaire comprised of the questions related to the comparison of the restaurant selection process that they followed before the experiment and the restaurant suggestion process of the implemented in-car navigation system. It obtained user feedback on user experience, efficiency, and accuracy of the implemented system.

3.3.1 User experience

To capture the user experience while interacting with the implemented in-car navigation system, questions related to the following aspects were inserted into the questionnaire.

1. Procedure - Questions related to the procedure focus on the overall procedure of restaurant suggestions.
2. Robot design - Questions related to the robot design focus on whether the user feels the implemented design complies with system requirements and whether the user has been able to differentiate the robots of multiparty conversation with the help of the design.

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3. Robot animations - Questions related to the robot animations focus on whether the implemented animations are suitable to the defined scenarios of both robots in idle, both robots listen, the left robot speaks while the right robot listens and the right robot speaks while the left robot listens.
4. Listening experience - Questions related to the listening experience focused on the dialogues used in the conversation of robots to convey the relevant information, whether the user has been able to identify two different voices of the robots and users' opinions about the conversation.
5. Speaking experience - Questions related to the speaking experience focused on whether the users' responses were identified by the system and users' opinions about the user's engagement in the conversation.

3.3.2 Efficiency and accuracy

The efficiency and accuracy of the system are measured based on the efficiency and accuracy of the restaurant suggestion. It asked the user for feedback on how accurately the system was able to provide a suggestion to the user based on his/her preference. Furthermore, the users' feedback was obtained about the quality of the information provided in the conversation regarding a particular restaurant and whether the provided information is sufficient to decide whether to go to the restaurant that is selected by the system.

4. Results

4.1 Results of the speech misdetections

It can be observed that the maximum number of speech misdetections observed in the system is 2. It resulted in a total of 8 speech misdetections throughout 15 experiments. In each experiment there were 5 speech occurrences which resulted in 75 total speech occurrences during 15 experiments, so that there were 67 correctly detected speeches throughout 15 experiments.

The accuracy of speech detection can be calculated as follows.

Accuracy of speech detection = (Total number of correctly detected speeches / Total number of speech occurrences) × 100%

$$= (67 / (15 \times 5)) \times 100\%$$
$$= 89.33\%$$

These results depict that the implemented system is quite accurate in obtaining the conversations of users. It is observed that the main reason behind the speech misdetections is the time delay that it takes to obtain the user input after the conversations of the robots. Even though the time delay between obtaining user input and the conversations of the robots is less than two seconds, most of the participants who experienced speech midsection during the experiments, gave their user input before the detection period which resulted in it being a speech misdetection.

4.2 Results of the facial expressions analysis

The obtained results are depicted in Figure 7.

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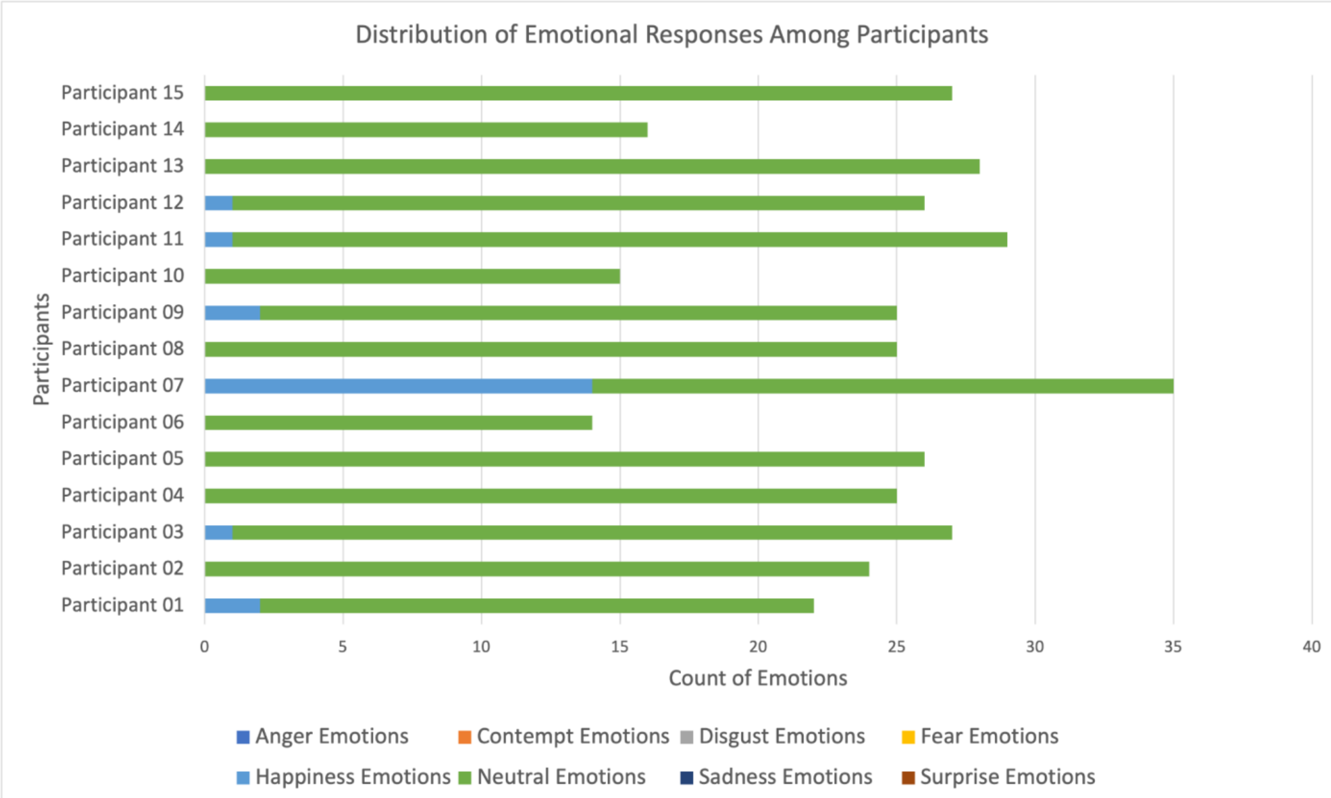

Figure 7: Distribution of Emotional Response Among Participants

It can be observed that neutral emotions were observed most of the time from almost all of the participants. Other than neutral emotions, some participants showed happy emotions. The total amount of neutral emotions was 345 which resulted in an average of 23 neutral emotions per participant. The total amount of happy emotions was 21 which resulted in an average of 1.4 happy emotions per participant. Even though the emotion classification algorithm could identify all the other mentioned emotions, none of them were identified from all the participants. It is observed that some participants took higher engagement time with the system due to speech misdetections and they tend to have a higher amount of emotion count than other participants. Furthermore, due to the lighting conditions and placement of the web camera of the laptop, some of the captured emotions were not classified properly.

4.3 Results of the user feedback

15 user feedback obtained on various aspects of the implemented system is summarized in Table 1.

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Table 1: User feedback obtained on various aspects of the system.

Category	**Scale**	**Results**
Restaurant Suggestion Convenience	1 (Very Inconvenient) to 5 (Very Convenient)	Rating 4: 5/15 Rating 5: 10/15
Overall Restaurant Suggestion Procedure	1 (Poor) to 5 (Great)	Rating 4: 8/15 Rating 5: 7/15
First Impression of Robot Design	Strongly Disagree to Strongly Agree	Strongly Agree: 7/15 Agree: 7/15 Neutral: 1/15
Differentiation of Two Robots by Design	Strongly Disagree to Strongly Agree	Strongly Agree: 7/15 Agree: 8/15
Ratings for Robot Animations - Idle	1 (Highly Unsuitable) to 5 (Highly Suitable)	Rating 5: 8/15 Rating 4: 5/15 Rating 3: 2/15
Ratings for Robot Animations - Listening	1 (Highly Unsuitable) to 5 (Highly Suitable)	Rating 5: 7/15 Rating 4: 8/15
Ratings for Robot Animations - Speaking & Listening	1 (Highly Unsuitable) to 5 (Highly Suitable)	Rating 5: 8/15 Rating 4: 6/15 Rating 3: 1/15
Listening Experience - Conversation Clarity	Strongly Disagree to Strongly Agree	Strongly Agree: 11/15 Agree: 4/15
Listening Experience - Conversation Flow	Strongly Disagree to Strongly Agree	Strongly Agree: 3/15 Agree: 11/15 Neutral: 1/15
Listening Experience - Differentiation by Voice	Strongly Disagree to Strongly Agree	Strongly Agree: 9/15 Agree: 5/15 Neutral: 1/15
Speaking Experience with the System	1 (Poor) to 5 (Great)	Rating 5: 11/15 Rating 4: 4/15
Efficiency and Accuracy - Restaurant Selection Accuracy	1 (Poor) to 5 (Great)	Rating 5: 8/15 Rating 4: 7/15
Efficiency and Accuracy - Decision to Visit	Strongly Disagree to Strongly Agree	Strongly Agree: 4/15 Agree: 10/15 Neutral: 1/15
Efficiency and Accuracy - Comparison to Manual	Highly Inconvenient to Highly Convenient	Highly Convenient: 8/15 Somewhat Convenient: 7/15

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5. Discussion

It was observed that users have given positive feedback on the convenience of finding a restaurant through the implemented system. The idea of getting only the required details for the restaurant suggestion has proved to be a better approach than getting many details from the user that are not that relevant to the restaurant suggestion. Thus, the same procedure can be followed when enhancing the user experience of the system further. Overall restaurant suggestion procedure has to be optimized as there is a significant number of ratings of 4 than ratings of 5. Revising the design of the implemented system to get more user attraction with an increased positive first impression to the user should be considered. It is believed that due to the two distinct shapes, the user has identified the two robots through the design. Finding a more feasible way to increase the attraction to the user while maintaining the ability to differentiate two robots with the help of the two designs should also be considered. The results show revising both robots in idle animation and one robot speaks while the other robots listen to animation can be considered. Furthermore, both robots listening animations have got a higher suitability rating compared to other animations. As the majority of the users strongly agreed that the structure and wording of the conversation were clear enough to understand and were well organized in the implemented system, it can be identified that smaller conversations with more commonly used words tend to make conversations clearer and more understandable. Optimizing the flow of the conversation to make the conversations more attractive considering the distribution of the feedback on the statement "The flow of conversation did not make the experience boring" may be feasible. As the majority of the participants strongly agreed that they have differentiated two robots with the help of two voices, using a female voice and a male voice to represent two different robots tends to be an effective approach. As the majority of the users have rated their engagement in the conversation as great, the approach of allowing the user to express what he wants and adapt the conversation according to that tends to become an attractive approach.

Considering the results of the speech misdetections, it can be observed that the implemented system has higher accuracy in speech detection. It is observed that most of the speech misdetections occurred because there is a delay in obtaining user input after the conversation of the robots. This delay was reduced to less than 2 seconds after some modification to the system architecture. Furthermore, it was observed that this delay depends on the system's performance as well. The results of the facial expression analysis of the participants show that the majority of the participant showed neutral expressions while engaging with the system whereas some participants have shown happy emotions. From these results, one can predict that this system will not distract the driver in real-world conditions, neither will it try to obtain greater attention of the driver which will make the driver concentrate less on driving. Considering the user feedback, the majority of the participants of the experiment rated great for the accuracy of the restaurant selection process based on/her preference. Furthermore, they have also strongly agreed with the statement "Decided whether to go to that restaurant based on the conversation and obtained sufficient details to make the decision". These results depict that the system has higher accuracy in suggesting the system and providing enough information to select a restaurant whereas the approach of providing only the key information on selecting a restaurant other than providing all the information that the system has on a particular restaurant, tends to become a more effective approach. Making the conversation less boring was one of the main intentions of providing the user with only the key information on the restaurants. Finally, with the results of the convince of the implemented system compared to the manual restaurant finding procedure, it can be observed that almost all the participants experienced an elevated convenience with the implemented system whereas the majority of the participants stated that the implemented system is highly convenient than the manual procedure. With this result, the concept that the implemented system tried to convey seems to be more practical in terms of real-world implementations.

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6. Conclusion

In conclusion, the implemented in-car navigation system focusing on restaurant suggestions has shown enhanced convenience compared to manual procedures of restaurant suggestions. With the obtained results, the implemented system shows higher accuracy in speech detection and multiparty conversations while minimizing the distraction to the user. The design of the system was accepted by the users the system and some of the possible optimizations on animations were identified. With the highly rated listening and speaking experience, users have witnessed a useful multiparty conversation that ultimately provided them with sufficient details on selecting a restaurant based on/her preferences. Even though a predefined dataset of restaurants for restaurant suggestions has been used due to the limited amount of information from Google places service on restaurants, it has effectively provided restaurants according to the preference of the user which enhanced the user experience aspects of the implemented system.

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