Profiled with Purpose: LLMs’ Role in User Profiles for Personalized Conversations

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The advent of Large Language Models (LLMs) has revolutionized Human-Robot Interaction (HRI), especially in developing social robots that can engage in personalized conversations with older adults. We discuss an approach utilizing LLMs to generate dynamic user profiles by analyzing interactions between the robot and the user as a part of a larger project to develop a conversational robot that can assist older adults in recognizing and maintaining their ikigai (sense of meaning and purpose in life) by providing personalized interaction and engagement, however, achieving this level of personalization requires collecting user data based on what the user discusses during the conversation. The concept of user-oriented HRI emphasizes designing interfaces that cater to individual users by profiling based on characteristics and preferences hence enabling robots to adapt in behavior to ensure naturalness in interaction and enhancing user experience as adaptability plays an important role in the Almere model of the acceptance of assistive social robots by older adults [4, 8]. A user profile represents a set of information about a user, including rules, settings, needs, interests, behaviors, and preferences [2]. This information can be static or dynamic data; static attributes of the data refer to relatively unchanged data like name, gender, where they live, their occupation, etc, and dynamic data can be interests and hobbies or sentiments that may change over time.

A user profiling survey suggests using machine and deep learning algorithms, filtering techniques, statistical modeling, and ontology-based methods to extract user profiling features [3]. A study developed a combination of k-means clustering Variational Autoencoder (VAE) and Generative Adversarial Network (GAN) to generate words used for modeling user preferenceand Dempster-Shafer theory was adopted for evidential modeling to infer user profiles [6]. Then the introduction of Large Language Models (LLMs) expanded the ability in natural language understanding; researchers have explored how LLMs can reason through user activities and describe their interests in nuanced and interesting ways, similar to how a human would. Building upon the framework introduced in [1] for personalized extraction of interest journey using techniques like few-shot prompting, prompt-tuning, and fine-tuning, our study extends this approach by prompting the LLM to use dialogues from the interaction between the robot and the user to generate user profiles that capture user’s interests. The user’s profile generated is then used in future interactions as a conversation starter.

For each user, data is collected in six categories:

(1) **Locations**: User’s residence, frequent locations visited, previous residence
(2) **Personal connections** (names/nicknames/relation to the user, activities the user does with them, feelings towards the person, are they living, memories with them): Family, friends, pets, colleagues
(3) **Activities**: Daily schedule, hobbies, job (working or retired)
(4) **Health**: Everyday well-being, health conditions
(5) **Life Events**: Current events, past events, goals
(6) **Discussed Topics** (Other topics that the user discussed)

The categories are chosen based on the sources of ikigai that are of 3 levels—first person (personal; eg, hobbies), second person (interpersonal; eg, family), and third person (community; eg, volunteering) [7].

After the conversation with the robot, the user and robot dialogue is fed into the LLM as input with a prompt, and the user profile is updated after every conversation. In our study, we are using the GPT-4 model as the LLM. The prompt used to generate the user profile:

“*action = [’role’: ’system’, ’content’: f”’Summarize and extract information from the following chat log between agent and user in: {summary_all}. Put the data about the user only into a nested JSON list. Do not change the format and order of the keys, include all the keys in the output and if any value for the key is not mentioned in the chat log the value will be saved as “ ”. The outer keys are ’User_information’,*

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```
{
    "User_information": {
      "name": "P1",
      "nicknames": " ",
      "age": " "
    },
    "Location": {
      "current_residence": "Bloomington",
      "previously_lived": "California, Ferney-Voltaire in France",
      "frequent_locationsVisited": "CERN, France and Switzerland, England, Wales",
      "locations_travelled": "California, England, Wales"
    },
    "Personal_connections": {
      "family": {
        "name": "Husband, Son, Daughter, Brother (deceased)",
        "relationship to user": "Husband, Son, Daughter, Brother",
        "feelings towards that person/pet": "Memories with husband, memories with daughter, brother's death had a significant impact",
        "shared activities/events": "Travelled with husband and son, shared photo with daughter",
        "shared interests": "Shape note singing with husband",
        "important things for family member/friend/pet/colleagues": "Husband's work at CERN, Son's role as navigator during family trip"
      },
    "Activities": {
      "daily_schedule": " ",
      "hobbies": "Shape note singing",
      "job(working/retired)": "Husband worked at Physics and CERN"
    },
    "Health": {
      "everyday_wellbeing": " ",
      "health_conditions": " "
    },
    "Life_events": {
      "current events": "Sharing memories with daughter",
      "past events": "Husband's work at CERN, family trip to California, shape note singing trips to England",
      "goals": " "
    },
    "Discussed_topics": {
      "1 sentence summary of topics": "Discussed family travels, experiences with late husband, shape-note singing trip",
      "important values to user": "Family, memories with husband, shape note singing",
      "topics user is passionate about": "Shape note singing, family travels",
      "topics that make they sad or upset": "Loss of husband and brother"
    }
  }
```


Fig. 1. Sample JSON output of the user profile

'Location', 'Personal_connections', 'Activities', 'Health', 'Life_events', 'Discussed_topics', 'date', 'time'. Inside 'User_information' the keys are 'name', 'nicknames', 'age'. Inside 'Locations' the keys are 'current_residence', 'previously_lived', 'frequent_locationsVisited', 'locations_travelled. Inside 'Personal_connections' the keys are 'family', 'friends', 'pets' and 'colleagues'. The keys 'family', 'friends', 'pets' and 'colleagues' should have sub categories including 'name', 'relationship to user', 'feelings towards that person/pet', 'shared activities/events', 'shared interests', 'important things for family member/friend/pet/colleagues'. Inside Activities the keys are 'daily_schedule', 'hobbies', 'job(working/retired)'. Inside Health keys are 'everyday_wellbeing', 'health_conditions'. Inside 'Life events' the keys are 'current events', 'past events', 'goals'. Inside 'Discussed_topics' the keys are '1 sentence summary of topics', 'important values to user', 'topics user is passionate about', 'topics that make they sad or upset' Add keys 'date', 'time' from {conv_time} "'] "

The prompt is based on the six categories listed and has the name of every key in the JSON dictionary, "{summary_all}" in the prompt refers to the dialogues. Example of dialogues:

Robot: Wow, that's a great picture! I really like it. Can you tell me what was happening when it was taken?

User: *This is a picture of my husband. We were on a trip near his workplace in France. We went to this geological formation which is called a plunging syncline. My husband is in his typical work clothes, his brown boots, his khakis, his long-sleeved shirt.*

Robot: Thank you for sharing such an amazing picture. It's very special to you, I can tell. You said that this was taken near your husband's workplace in France. Could you tell me the exact location?

User: *Well, the research place is called CERN, it's in France and Switzerland. His team had an apartment in France, a town called Ferney-Voltaire. He did several days of taking data and then he had vacation time, so that was how the two of us could go to where this picture was taken. And I think the picture is in the mountains in France, would be southwest of Ferney-Voltaire.*

Robot: Thank you for providing such a detailed answer! It sounds like you had a wonderful time taking this special picture. Do you remember the name of the mountain or mountain range where you took the picture?

User: *No, I don't. I just remember the plunging syncline because my brother showed me a plunging syncline on the California Pacific coast about 20 or 30 years earlier.*

The output contains all the keys listed in the prompt and the values from the conversation. In this case, the user talks about her time in Switzerland, traveling with her family, and the memories attached. The generated output Figure 1 is well structured and captures all the nuances of the conversation and necessary information about the user that can personalize future conversations. For example, when the user talks to the robot again, the robot could ask questions about the user's time in Switzerland. The use of LLMs raises some reliability concerns. The noted downside can be the model hallucinating that is making up or generating responses unrelated to the input [9]. Other than manually checking for hallucinations by comparing the input and output, studies have been done to quantify hallucination by using mathematical analysis of hallucination in GPT models. It rigorously defines and measures hallucination and creativity using concepts from probability theory and information theory [5]. In conclusion, these advanced models have the potential to craft dynamic user profiles from conversational data, thereby enabling robots to conduct more meaningful interactions. This can play a crucial role in assisting older adults to find and sustain their ikigai. Future work related to this study is to find innovative solutions to address challenges such as hallucinations to build a balance between personalization, user privacy, and ethical considerations to fully realize the benefits of LLMs in enhancing the lives of older adults through personalized HRI.

CCS Concepts: • **Human-centered computing → User centered design**; **User centered design**.

Additional Key Words and Phrases: Human-Robot Interaction, HRI, user profile, personalized conversation, older adults, social robots, Large Language Model, GPT-4

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