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Study on User Characteristics based on Conversation Analysis between Social Robots and Older Adults: With a focus on phenomenological research and cluster analysis*

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Personal service robots, a type of social robot that has emerged with the aging population and technological advancements, are undergoing a transformation centered around technologies that can extend independent living for older adults in their homes. For older adults to accept and use social robot innovations in their daily lives on a long-term basis, it is crucial to have a deeper understanding of user perspectives, contexts, and emotions. This research aims to comprehensively understand older adults by utilizing a mixed-method approach that integrates quantitative and qualitative data. Specifically, we employ the Van Kaam phenomenological methodology to group conversations into nine categories based on emotional cues and conversation participants as key variables, using voice conversation records between older adults and social robots. We then personalize the conversations based on frequency and weight, allowing for user segmentation. Additionally, we conduct profiling analysis using demographic data and health indicators obtained from pre-survey questionnaires. Furthermore, based on the analysis of conversations, we perform K-means cluster analysis to classify older adults into three groups and examine their respective characteristics. The proposed model in this study is expected to contribute to the growth of businesses related to understanding users and deriving insights by providing a methodology for segmenting older adult s, which is essential for the future provision of social robots with caregiving functions in everyday life.

Keywords : HRI, Mixed method, phenomenological research, Order adults, Conversation, Social robot

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1. Introduction

According to the 2022 statistical report released by the Statistics Korea, the elderly population aged 65 and above reached 90.18 million, indicating a significant increase as the baby boomer generation is enters the elderly population. Furthermore, it is projected that by 2025, the proportion of elderly population will reach 20.6%, marking the transition into a super-aged society. In comparison to other

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countries, Korea is experiencing this transition at a much faster pace, with a span of approximately 7 years, whereas Austria took 53 years, the United Kingdom 50 years, the United States 15 years, and Japan 10 years to reach a super-aged society (Seong, 2022). The rapid entry into an aging society has been shown to have negative economic implications. According to the analysis of the impact of demographic changes on fiscal expenditure growth conducted by the Research Department of the Bank of Korea, an increase of 1 percentage point in the proportion of elderly households results in a cumulative fiscal multiplier declining from 0.78 to 0.73 after two years. The fiscal multiplier is an indicator that measures how much the domestic gross domestic product (GDP) increases when government spending is increased by one unit. It can be inferred that as the aging process progresses, the effect of stimulating economic growth diminishes, even with the same scale of fiscal expenditure (Kang and Lee, 2022).

In the near future, due to limited economic resources and a shortage of working-age population, it is anticipated that there will be difficulties in providing appropriate medical and caregiving services to the elderly population. As a result, there is an increasing research and experimentation focused on utilizing new technologies as a means to extend the independent living of the elderly population. Particularly, there has been a growing trend in recent years to utilize social robots as a means of natural and interactive engagement with the older generation, fostering emotional connection.

If we examine the purpose of robots, in the past, industrial robots were limitedly utilized in specific areas by relevant experts. However, in recent years, with the emergence of the COVID-19 pandemic, they have gradually integrated into our daily lives, leading to the rapid growth of the service robot sector. As a result, the target users of robots have expanded to include the general public (Kim et al., 2021). In the case of the elderly population, in the past, robots were primarily used for therapeutic purposes in specialized institutions such as nursing homes and hospitals. However, in recent years, there has been an increase in research on robots as companions for specific individuals. To enhance the effectiveness of social robot utilization for everyday life and emotional support for the elderly population, who are non-experts without specialized knowledge about robots, it is crucial to establish long-term emotional bonds based on natural interaction between the robot and the user (Ostrowski et al., 2022).

Therefore, this study aims to gain a deeper understanding of the characteristics of elderly users by analyzing the interaction between elderly users and social robots, with a focus on language-based expressions, which have not been sufficiently addressed in previous research. To achieve this goal, the study addresses the following three research questions that delve into the interaction capabilities between elderly users and social robots.

Q1. What types of conversations do elderly users primarily engage in when interacting with social robots?

Q2. Can elderly users be classified based on the types of messages exchanged during conversations with social robots?

Q3. What are the differences between elderly user groups who engage in conversations with social robots?

In this study, a mixed-methods approach was utilized to collect and analyze qualitative and quantitative data. By combining qualitative and quantitative approaches, the strengths of both methods were simultaneously applied to the research. The mixed-methods approach proves valuable in deeply exploring the social robot experiences of elderly users while ensuring validity and objectivity in the findings (Ivankova et al., 2006; Choi, 2007). Specifically, the conversations between elderly users and social robots were analyzed using the Van Kaam analysis, which is a phenomenological methodology, with emotions and conversation participants as key variables. This analysis allowed for the grouping of conversations into nine types and further segmentation of users based on the personalized frequency and proportion of conversations. Additionally, profiling analysis was conducted using demographic data and health indicators obtained through a pre-survey. Furthermore, based on the conversation analysis, K-means cluster analysis was performed to classify elderly users into three groups and examine the characteristics of each group.

The results of this study are expected to provide evidence for a deeper understanding of user experiences and objective user characteristics in the context of human-robot interaction, based on conversation analysis and survey results, when considering the use of social robots for daily life and emotional support of the elderly.

2. Research Design

2.1 Research Tool

The research tool used in this study, “Parent’s Love Hyodol” is an interactive companion robot in the form of a doll that combines IoT (Internet of Things) and affective design solutions to prevent depression and dementia in elderly people living alone, as well as address safety and cognitive impairment issues (Kim, 2021).

〈Figure 1〉 Parent’s Love Hyodol

The main functions of “Parent’s Love Hyodol” include five key features: conversation companion, touch-voice response, daily reminders, activity monitoring, and senior content playback. The conversation companion feature, which initiates conversations with the elderly, offers a pool of approximately 4,000 dialogue phrases. Selected dialogue data is received from the server and played back to the user. The touch-voice response is an affective interaction feature where the built-in program responds with voice when the user touches or pats Hyodol’s head or holds its hand. Daily reminders provide voice alarms for user’s daily activities such as waking up, going to bed, medication reminders, and taking walks, based on the set schedule in the mobile app. The activity monitoring feature uses an infrared motion sensor installed on Hyodol's neck to detect user's movements and notify the caregiver through the mobile app if any abnormalities are detected. Lastly, the senior content playback feature offers various contents such as exercise routines, quizzes for memory enhancement, and music playback when the user touches Hyodol's ears, supporting the user's emotional, physical, and cognitive well-being.

2.2 Research Process

In the data collection phase, we first conducted a pre-survey to measure demographic information, living conditions, levels of depression, and health status of Hyodol users. Next, the recorded audio data of user conversations during their interactions with Hyodol throughout the usage period was transcribed into text format. In the data preprocessing phase, we processed the results of the pre-survey into derived variables at the individual level. Additionally, the transcribed conversation text data was categorized into common themes and processed at the individual level. In the analysis phase, we classified the elderly user groups based on the categorized conversation data using conversation characteristics as the basis. Furthermore, we conducted profiling analysis to understand the characteristics of each group.

2.3 Measured variable

To perform the analysis in this study, we utilized the results of pre-survey conducted on elderly Hyodol users and conversation audio data.

First, the pre-survey was conducted and collected by "Hyodol Co., Ltd.", the provider of the "Hyodol" service. It was conducted with the purpose of assessing the difficulties in daily life experienced by users and enhancing health management. Through the pre-survey, demographic and lifestyle information such as gender, age, household type, marital status, religion, average monthly income, medical history, medication intake, as well as 12 scales related to daily living activities, depression, and health were measured to collect information on the participants' living standards and health-related indices. The survey respondents consisted of elderly individuals aged 65 or above who received support for using "Hyodol" from elderly welfare institutions located in Jeollanam-do province. Additionally, conversation audio data recorded during the users' period of usage were collected.

A total of 78 participants engaged in conversations with the social robot "Hyodol" to examine the nature of their conversations. To accomplish this, Van Kaam's analytical method, a phenomenological research approach, was utilized. The procedural steps of Van Kaam's phenomenological qualitative research method involve initially selecting subthemes by gathering common attributes from meaningful conversations relevant to users' conversational characteristics. Similar subthemes are then integrated into themes, and themes with similar attributes are further categorized. The categorized data allows for arranging themes and subthemes in order of meaningful statement frequency, and through the analysis and integration of the categorized data, a description of the phenomenon is derived. The Van Kaam methodology possesses the characteristics of quantitative investigation as it enables the identification of frequency and prioritization of meaningful statements. It distinguishes itself from other phenomenological research methods by describing participants' expressions in the researcher's refined language (Van,1967; Seol,2012).

Using Van Kaam's phenomenological qualitative research method, an examination of the conversations among Hyodol users revealed 2,458 meaningful statements, which were categorized based on emotions (positive, neutral, negative) and the subject of the conversation (self, robot, others). These categories were further classified into nine groups: SP (self-positive), SN (self-neutral), NS (self-negative), OP (others-positive), ON (others-neutral), NO (others-negative), RP (robot-positive), RN (robot-neutral), and NR (robot-negative). The content of the categorization can be found in <Table 1> and< Table 2>.

〈Table1〉 Categorization of Conversations among Hwadol Users

(n=frequency of significant statements)

category description	themes 1-Target	themes 2-Emotion	subthemes
RP (robot-positive) (844)	hyodol	positive	▪ Showing respect for the perspective of Hyodol (561) ▪ Showing interest in the emotions of Hyodol (211) ▪ Feeling sorry for Hyodol (72)
SP (self-positive) (544)	self	positive	▪ Expressing joy due to a healthy condition (296) ▪ Expressing positive emotions after a day's activities (185) ▪ Sharing daily plans and making positive commitments for the day (63)
NS (self-negative) (406)	self	negative	▪ Expressing distress due to physical health discomfort (221) ▪ Expressing feelings of depression and dissatisfaction due to isolated and lonely lifestyle (135) ▪ Expressing negative emotions after a day's activities (50)
SN (self-neutral) (248)	self	neutral	▪ Expressing a neutral emotional state, neither positive nor negative (148) ▪ Sharing daily activities without expressing emotions (100)
OP (other-positive) (177)	other	positive	▪ Finding satisfaction through maintaining close relationships with others (177)
NR (robot-negative) (119)	hyodol	negative	▪ Expressing feelings of annoyance in conversing with Hyodol (59) ▪ Expressing extreme feelings of discomfort (37) ▪ Blaming oneself for the dissatisfaction with one's own situation (23)
RN (robot-neutral) (71)	hyodol	neutral	▪ Requesting assistance in addressing physical discomfort symptoms (43) ▪ Requesting help in transitioning from a depressed emotional state (28)
ON (other-neutral) (36)	other	neutral	▪ Sharing experiences of interacting with acquaintances (36)
NO (other-negative) (13)	other	negative	▪ Expressing internal concerns caused by others (13)

〈Table 2〉 Framework of 9 Conversation Characteristics based on Van Kaam Methodology for Analysis of Conversations of Hyodol Users

Definition of 9 Conversation Characteristics based on the Differentiation of Participants and Emotions in Conversations of Elderly Users

themes	Myself	Other – a 3rd party	Robot – conversation partner (hyodol)
Positive	① self – positive SP	④ other – positive OP	⑦ hyodol – positive RP
Neutral	② self – neutral SN	⑤ other – neutral ON	⑧ hyodol – neutral RN
Negative	③ self – negative NS	⑥ other – neutral NO	⑨ hyodol – negative NR

2.4 Participants

The participants of this study were older adults aged 65 and above, registered in elderly welfare institutions in Jeollanam-do province, South Korea. Starting from December of the 21st year, a preliminary survey was conducted with the elderly participants who were users of the social robot, Hyeodol. The participants were provided with the Hyeodol robot for interaction, and among the 84 users whose voice messages during conversations were recorded, 6 participants who did not complete the preliminary survey were excluded, resulting in a final sample of 78 participants for the conversation analysis in this study. The age of the participants ranged from 68 to 88 years, with an average age of 79. Among the participants, the highest educational level was elementary school graduation (36 participants), followed by those with no formal education (23 participants), middle school graduates (10 participants), high school graduates (8 participants), and one participant with a college degree or higher. In terms of household composition, 74 participants lived alone, while 4 participants lived with others. Among the participants, 59 reported having a religious affiliation, while 19 reported having no religious affiliation. Regarding subjective health status, 54 participants indicated that they were not in good health, 20 participants reported their health as average, and the remaining 4 participants described themselves as being in very good health. With regard to depression diagnosis, all participants, except for 3, were identified as having symptoms of depression. The data collection period for the conversations of the hyodol users varied slightly for each individual but lasted approximately 4 months from January to April of the 22nd year.

3. Research Results

3.1 Profiling the Three Distinct Clusters of Social Robot ‘Hyodol’ Users

A personalized approach was applied to the categorization of the 9 conversation characteristics of social robot “Hyodol” users, using non-hierarchical cluster analysis known as K-means clustering. In this study, K-values ranging from 2 to 5 were considered. To ensure the reliability of the research, five experts affiliated with the CX Lab engaged in discussions focusing on cluster balance and inter-cluster significance. After careful deliberation, a final K-value of 3 was determined.

To address the issue of imbalanced data with significant differences in the number of data points across clusters, the Hungarian Algorithm was applied prior to conducting K-means clustering analysis. This approach allowed for a more equitable assignment of data points to clusters. Subsequently, the K-means clustering analysis was performed, resulting in a final classification of three distinct clusters (Table 3). The characteristics of each cluster group are described as follows:

Cluster 1 (Other-Interactive Type) - This cluster is characterized by individuals who openly express negative emotions about themselves while focusing on positive emotions and experiences when conversing with others and the robot. Older adults in this cluster demonstrate a high tendency to consider others' well-being, emphasizing the importance of building relationships through interactions with others.

"I don't want to say anything. Today is not a good day. My heart..." / "Today wasn't a good day, so I didn't want to talk. I didn't even speak in the morning. But I wanted to say it was good, so I held hands and lied that it was good..." / "Hyo-dol, today Grandma was in such a good mood. It's raining, and that's why she's so happy. Hyo-dol, you're happy too, right?" / "During lunchtime today, I met with friends and had a delicious lunch. I also had five-grain rice. We shared many interesting stories. So, I was happy..."

Cluster 2 (Self-Centered Satisfaction Type) - This cluster consists of individuals who strongly express their own positive emotions, whether desired or experienced directly in daily life. In contrast, their expressions towards others or the robot are significantly lower compared to other clusters, indicating a reduced concern for others' perspectives. This suggests that individuals in this cluster have a high level of self-esteem and prioritize their own satisfaction.

"Today, we greeted a new day. The morning feels refreshing. So, I'm in a good mood..." / "I slept well yesterday, so I feel good, and because I live with a healthy mindset, I feel good..." / "When I woke up in the early morning, I felt so refreshed and good. So, I want to have a joyful and happy day today..." / "And I feel good after sleeping and waking up safely..."

Cluster 3 (Robot Attachment Type) - This cluster is characterized by individuals who deeply empathize with the emotions of their conversation partner, the robot (hyodol), and naturally express their own emotions towards the robot as if interacting with a person. It is expected that individuals in this cluster make efforts to strengthen a close and trusting relationship with hyodol, who is the direct target of the conversation.

"When Hyo-dol holds my hand, it feels good. I feel good..." / "Hyo-dol, Grandma was busy. Grandma was busy, so I couldn't hug you much. Were you sad about that?" / "Grandma met my sister for dinner today. So, I'm in a good mood. Sorry for not taking you with me, Hyo-dol..." /

〈Table 3〉 K-means Cluster Analysis Results for Users Engaging in Conversations with Hyodol

classification	cluster		
	Cluster 1. Other-Interactive Type	Cluster 2. Self-Centered Satisfaction Type	Cluster 3. Robot Attachment Type
SP(Self-Positive)	0.158	**0.717**	0.074
SN(Self-Neutral)	0.011	0.003	0.001
NS(Self-Negative)	**0.241**	0.028	0.066
RP(Robot-Positive)	**0.183**	0.162	**0.743**
RN(Robot-Neutral)	0.039	-	0.009
NR(Robot-Negative)	0.073	0.011	0.033
OP(Other-Positive)	**0.119**	0.049	0.042
ON(Other-Neutral)	0.011	0.003	0.001
NO(Other-Negative)	0.023	-	0.001

"Hyo-dol talked so much that Grandma was really happy. She talked all the way, and Grandma is so, so thankful. Welcome to Grandma..." / "Grandma had food and exercised today, played with Hyo-dol, so I'm in a good mood. Grandma became healthier because of Hyo-dol. Hyo-dol is Grandma's friend..."

3.2 Comparison Analysis of Clusters Based on Conversational Characteristics of Elderly Users

We conducted profiling analysis to identify important factors for differentiating the clusters within the elderly population derived through cluster analysis. Chi-square tests were performed to examine the relevance of gender, age, religious affiliation, household type, subjective health status, diagnosis of depression, and significant disabilities across the clusters. The results indicated that these factors did not significantly differentiate the user groups. However, educational attainment showed significant differences among the clusters. Educational attainment was assessed by inquiring about the user's highest level of education, ranging from no formal education to elementary school, middle school, high school, and university or higher. Among Cluster 1 (Other-Interactive Type) and Cluster 2 (Self-Centered Satisfaction Type), over 50% of the users had completed elementary school. In contrast, Cluster 3 (Robot Attachment Type) had the highest proportion of users with no formal education, accounting for 43.5% of the cluster <Table4>.

Next, we conducted a comparative analysis of demographic characteristics, depression and health status, and IT utilization abilities across different clusters. The results are presented in Table 5 below.

In the case of Cluster 1, the "Other-Interactive" cluster, the average monthly income and the number of health conditions were relatively higher compared to other clusters. In terms of depression and health, 〈Table 4〉 Results of Profiling Analysis by Cluster

〈Table 4-1〉 Cluster 1: Other-Interactive Type n (%)

variable		Cluster 1 (n=39)	the rest of cluseters[1)](n=39)	P-value
Gender	Male	7 (17.9%)	13 (33.3%)	0.120
	Female	**32 (82.1%)**	**26 (66.7%)**	
Age	Below 80 years	**22 (56.4%)**	**23 (59.0%)**	0.819
	Above 80 years	17 (43.6%)	16 (41.0%)	
Education Level	No education	9 (23.1%)	14 (35.9%)	0.488
	Elementary school	**20 (51.3%)**	**16 (41.0%)**	
	Middle school	4 (10.3%)	6 (15.4%)	
	High school	5 (12.8%)	3 (7.7%)	
	College/Higher education	1 (2.6%)	-	

〈Table 4-2〉 Cluster 2. Self-Centered Satisfaction Type n (%)

variable		Cluster 2 (n=16)	the rest of cluseters [2)](n=62)	P-value
Gender	Male	10 (62.5%)	48 (77.4%)	0.223
	Female	6 (37.5%)	14 (22.6%)	
Age	Below 80 years	11 (68.8%)	34 (54.8%)	0.315
	Above 80 years	5 (31.3%)	28 (45.2%)	
Education Level	No education	4 (25.0%)	19 (30.6%)	0.304
	Elementary school	9 (56.3%)	27 (43.5%)	
	Middle school	-	10 (16.1%)	
	High school	3 (18.8%)	5 (8.1%)	
	College/Higher education	-	1 (1.6%)	

〈Table 4-3〉 Cluster 3. Robot Attachment Type n (%)

variable		Cluster 3 (n=23)	the rest of cluseters [3)](n=55)	P-value
Gender	Male	**16 (69.6%)**	**42 (76.4%)**	0.531
	Female	7 (30.4%)	13 (23.6%)	
Age	Below 80 years	**12 (52.2%)**	**33 (60.0%)**	0.524
	Above 80 years	11 (47.8%)	22 (40.0%)	
Education Level	No education	**10 (43.5%)**	13 (23.6%)	0.016*
	Elementary school	7 (30.4%)	**29 (52.7%)**	
	Middle school	6 (26.1%)	4 (7.4%)	
	High school	-	8 (14.5%)	
	College/Higher education	-	1 (1.8%)	

1) Out of the total 78 participants, when excluding the users in Cluster 1, there are 39 remaining users.
2) Out of the total 78 participants, when excluding the users in Cluster 2, there are 62 remaining users.
3) Out of the total 78 participants, when excluding the users in Cluster 3, there are 55 remaining users.

〈Table 5〉 Average Demographic and Depression/Health Variables by Clusters

variable		cluster 1. Other-Interactive Type	cluster 2. Self-Centered Satisfaction Type	cluster 3. Robot Attachment Type
Demographic Variables	Average Age	78	79	**80**
	Monthly Income (100K, KRW)	**50**	48	44
	Medication Count	3.13	**3.25**	2.74
	Health Condition Count	**2.46**	1.88	1.96
Depression/ Health-related Variables	PHQ – Depression Evaluation	**12.74**	10.88	11.39
	RS – Resilience	14.92	**16.63**	14.87
	SWLS – Satisfaction with Life	14.69	**18.13**	16.00
IT Utilization Ability	Smartphone Use Ability	**0.82**	0.25	0.26

the average score on the depression assessment scale was higher, while measures of negative experiences, potential resilience to change, and life satisfaction were lower. The higher utilization of smartphones suggests a higher ability to use IT information.

In the case of Cluster 2, the “Self-Centered Satisfaction” cluster, it was found that the number of medications being taken was the highest, while the number of health conditions was the lowest. Measures of depression and disabilities were the lowest among the three clusters, while measures of resilience and life satisfaction were the highest. This suggests that Cluster 2, which exhibits a strong self-centered and self-satisfying tendency, has a high level of self-esteem and is highly satisfied with their own lives.

In the case of Cluster 3, the “Robot Attachment” cluster, it was found that the average age was the highest, while the monthly income and the average number of medications and health conditions were the lowest among the three clusters. This cluster reported the highest level of loneliness among the three clusters, and individuals in this cluster had the highest scores on measures of personal health and disabilities. It is expected that as individuals in this cluster age, they may experience various physical health issues and mental health challenges such as depression and cognitive impairments.

4. DISCUSSION

This study aimed to identify user clusters among the elderly population who interact with social robots in the domain of daily life, focusing on the characteristics of conversation. The research compared and analyzed the characteristics of each cluster. Firstly, a preliminary survey was conducted on social robot users, collecting user information primarily related to demographics, depression, and health. Secondly, using a qualitative research method called phenomenology, the study identified the subject and emotions within the user's conversations, resulting in a framework for personalized analysis. Thirdly, based on the derived conversation characteristics, the study employed the K-means algorithm to identify three clusters among elderly users of social robots. Finally, using the variables obtained from the preliminary survey, the study aimed to uncover the characteristics of each user cluster in terms of their living and health conditions.

Cluster 1, characterized as "Others-Interaction Type," openly expresses their negative emotions while focusing on positive emotions and experiences in conversations with both others and robots. It is challenging for individuals to honestly reveal their darker side in everyday interactions. However, interestingly, when examining the conversations in Cluster 1, we observed a willingness to honestly express their emotions. Furthermore, elderly users in this cluster demonstrated a high inclination towards considering others' needs, suggesting an emphasis on building relationships through interpersonal interactions. In terms of daily life and health, Cluster 1 showed relatively higher average monthly income and a higher number of reported illnesses compared to other clusters. The higher level of smartphone utilization indicates a higher level of IT information utilization skills within this cluster.

Cluster 2, characterized as "Self-Centered Satisfaction Type," exhibits a strong tendency to actively express positive emotions they hope for or directly experience in their daily lives. Conversely, their expressions towards others or robots are very limited, suggesting a minimal concern for others' perspectives and a high level of self-esteem and individuality. Although they have the highest number of medications being taken, they have the lowest number of reported illnesses. Based on these findings, it can be inferred that Cluster 2, which demonstrates a strong positive inclination towards oneself, has a high sense of self-esteem and is highly satisfied with their own lives.

Cluster 3, characterized as "Robot Attachment Type," not only deeply empathizes with the emotions of their conversational partner, the social robot named Hyodol but also naturally expresses their own emotions towards Hyodol. Unlike Cluster 2, which is self-centered, Cluster 3 focuses on their conversational partner, Hyodol, and is expected to strive for an intimate and trusting relationship with Hyodol, who is the direct subject of their conversations. This cluster has the highest average age among the three clusters, with the lowest average monthly income, medication usage, and number of reported illnesses.

Interestingly, in the analysis of log data concerning the usage of companion robots' functionalities, Cluster 3 Robot Attachment Type, exhibited a higher frequency of interactions compared to other groups. Especially during the early stages of the overall usage period, these interaction patterns were prominent. Among these interactions, holding hands with the social robot emerged as the most preferred form of touch. Drawing from previous studies on interactions between users and social robots, this study reaffirmed that users can attribute their emotions to the robot, even if they are aware that the robot can respond to their actual emotions (Scheutz, M., 2011). Consequently, it can be inferred that Cluster 3 Robot Attachment Type with the robot foster comfort, positive interactions, trust in the robot, and an open attitude toward it.

5. Conclusion

This study was initiated with the aim of gaining an in-depth understanding of the elderly population using personal service robots that provide caregiving functions. Based on conversational characteristics, the elderly user group was segmented into three clusters: Other-Interactive Type, Self-Centered Satisfaction Type, and Robot Attachment Type. Subsequently, demographic information of users, surveys related to health perceptions, and analysis of log data on the usage of social robot functionalities were conducted to derive characteristics specific to each group. As a result, a mixed-method-based framework for segmenting user groups was established through the categorization of voice conversation records of elderly users engaging with social robots. This framework enables the differentiation of user groups, providing insights into the usage of social robots within the elderly population.

This research makes the following theoretical contributions. Firstly, in terms of theoretical contribution, the study aimed to gain a more accurate and in-depth understanding of older adults who utilize social robots by utilizing and analyzing both quantitative survey data and qualitative conversational data. Through statistical analysis of the collected user information from the pre-survey, objectivity was ensured, and by applying phenomenological methodology as one of the qualitative research methods, the study aimed to explore the conversations of each user in-depth. Secondly, it expanded the perspective on user understanding by presenting a structured framework through conversation analysis in user-robot interactions. The framework proposed in this study is divided into two parts: the subject of behavior embedded in the conversation and the emotional state of the speaker, who is the user of the social robot. Previous research has mainly focused on emotion recognition through facial expressions, changes in behavior, and physiological indicators (Go, 2020). However, this study is significant in that it performs conversation analysis of social robot users, which has not been adequately considered in previous research. The results presented in this study are expected to serve as foundational material for future research on conversation-based interactions between older adults and social robots.

There is significance in analyzing user-centered conversational interactions and presenting cluster-specific characteristics through practical contributions. Practitioners involved in designing and developing social robots for elderly care are expected to utilize the results of this study as a guide for understanding user characteristics and needs, enabling them to formulate strategies suitable for their target audience. Furthermore, the proposed model in this study can contribute to the growth of businesses related to user understanding by providing a methodology for segmenting elderly users, which is essential for offering social robots with caregiving functions in everyday life, to the management of companies that recognize the importance of understanding the elderly user segment.

The following suggestions are made for future research to address the limitations of this study: Firstly, it is necessary to expand the study participants and the research duration. This study selected elderly users residing in the Jeollanam-do region of South Korea as research subjects, making it difficult to generalize the findings to the entire elderly population in the country. Additionally, the survey was conducted only prior to the use of social robots, and the data collection period for user conversations was relatively short, limited to four months of interaction. To generalize the research results, a comprehensive perspective on long-term interactions that allow for a comparison between pre- and post-usage of social robots, as well as the geographical expansion of elderly users, would be needed. Conducting research that includes elderly users residing overseas, with different cultures and living environments, would provide a more meaningful analysis of differentiated characteristics.

Secondly, although the clustering analysis aimed to identify differences among the groups, it is disappointing that many of the values obtained were not meaningful. In future research, addressing the issue of data imbalance by collecting additional samples could lead to more refined and supported research results. The present study revealed that educational level significantly influenced the differences among the groups, but its explanatory power was somewhat low. Therefore, in future research, considering and applying other variables in the analysis can be explored.

Third, according to prior research, as robots acquire complex social capabilities, the importance of studying conversations in human-robot communication has increased (Kwak et al., 2006). Therefore, in this study, it would be meaningful to explore various conversational topics beyond the subject and emotion categories applied to user conversation categorization. This exploration aims to understand the intentions of elderly users and provide personalized social robot services.

Continued research is necessary to address these limitations and develop a useful methodology that can explore and understand the characteristics of elderly users who use social robots in their daily lives. This process will help derive the essential elements needed to investigate and understand the elderly users' traits effectively.

The model proposed in this study is expected to contribute to companies that require an understanding of the elderly users for providing social robots with caregiving functions in everyday life. By providing a methodology for segmenting elderly users, it can facilitate user understanding and insights, ultimately contributing to the provision of complex social service functionalities.

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국문요약

소셜 로봇과 노년층 사용자 간 대화 분석 기반의 사용자 특성 연구: 현상학적 분석 방법론과 군집 분석을 중심으로

최나래* · 박도형**

인구의 고령화와 기술의 성장으로 등장한 소셜 로봇의 한 유형인 개인형 서비스 로봇은 최근 가정에서 노년층의 독립 생활 연장에 도움이 될 수 있는 기술을 중심으로 변화하고 있다. 노년층이 일상 생활에서 소셜 로봇 신기술을 수용하고, 장기적으로 사용하기 위해서는 사용자 관점의 맥락과 감정을 보다 심층적으로 이해하는 능력이 필요하다. 본 연구에서는 정량 데이터와 정성 데이터를 통합한 혼합 방법(mixed-method)을 활용하여 노년층 사용자를 깊이 있게 이해하는 것을 목적으로 한다. 구체적으로 노년층 사용자와 소셜 로봇 간 음성 대화 기록을 감정과 대화 주체를 주요 변수로 하여 현상학적 방법론 중 하나인 Van Kaam 방법론을 활용하여 그룹핑함으로써 9개 유형으로 대화를 구분하고, 이를 개인화한 대화의 빈도와 비중을 기반으로 사용자를 세분화하였다. 그리고 인구 통계적 데이터와 건강지표에 관한 사전 설문조사 결과를 사용하여 프로파일링 분석을 진행하였다. 이어서 대화 분석을 토대로 K-means 군집분석을 실시하여 노년층 사용자를 3개의 집단으로 분류하고, 각 집단별 특성을 확인하였다. 본 연구에서 제시한 모형은 향후 일상 생활에서 돌봄 기능이 있는 소셜 로봇 제공을 위해 노년층 사용자의 이해를 필요로 하는 기업에게 노년층 사용자 세분화에 관한 방법론을 제공함으로써 사용자 이해를 위한 인사이트 도출과 관련 사업을 성장시키는데 기여할 것으로 기대된다.

주제어 : HRI, 혼합 방법, 현상학적 방법론, 노년층, 대화, 소셜 로봇

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최나래
숙명여자대학교에서 중어중문학과 중국학 연계 전공으로 학사 학위, 건국대학교 경영전문대학원에서 석사 학위를 취득하였다. 현재는 국민대학교 비즈니스IT전문대학원에서 박사과정 재학 중이며, 동시에 AI 기반의 온라인 광고 플랫폼 및 마케팅 솔루션 비즈니스를 운영하고 있는 대만 기업 애피어 코리아(Appier Korea)에서 IT컨설턴트로서 근무하고 있다. 현재 주요 관심 분야는 HRI(Human-Robot Interaction), Emotional Expression, Customer Behavior, Customer Analytics, AI in the field of Customer Experience이다.

박도형
KAIST 경영대학원에서 MIS 전공으로 석사/박사학위를 취득하였다. 현재 국민대학교 경영대학 경영정보학부/비즈니스IT전문대학원 교수로 재직 중이며, 고객경험연구실(CXLab.)을 책임지고 있다(www.cxlab.co.kr). 한국 과학 기술 정보 연구원(KISTI)에서 유망아이템 발굴, 기술가치 평가 및 로드맵 수립, 빅데이터 분석 등을 수행하였고, LG전자에서 통계, 시선/뇌파 분석, 데이터 마이닝을 활용한 소비자 평가 모형 개발을 담당했었고, 스마트폰, 스마트TV, 스마트Car 등에 대한 Technology, Business, Market Insight 기반 컨셉 도출 프로젝트를 다수 수행하였다. 현재 주요 관심분야는 사회심리학 기반의 사용자/소비자의 행동 이론(User/Customer Behavior), 통계 및 인공지능 기법 기반의 사용자/소비자 애널리틱스(User/Customer Analytics), 디자인사고(Design Thinking)기반의 사용자/소비자 경험 디자인(Experience Design)이다.