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A Study on Consumer Emotion for Social Robot Appearance Design: Focusing on Multidimensional Scaling (MDS) and Cluster Analysis* **

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In order for social robots to take root in human life, it is important to consider the technical implementation of social robots and human psychology toward social robots. This study aimed to derive potential social robot clusters based on the emotions consumers feel about social robot appearance design, and to identify and compare important design characteristics and emotional differences of each cluster. In our study, we established a social robot emotion framework to measure and evaluate the emotions consumers feel about social robots, and evaluated the emotions of social robot designs based on the semantic differential method, an kansei engineering approach. We classified 30 social robots into 4 clusters by conducting a multidimensional scaling method and K-means cluster analysis based on the emotion evaluation results, confirmed the characteristics of design elements for each cluster, and conducted a comparative analysis on consumer emotions. We proposed a strategic direction for successful social robot design and development from a human-centered perspective based on the design characteristics and emotional differences derived for each cluster.

Keywords : social robot, social robot design, kansei engineering, semantic differential method

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1. Introduction

Social robots are intelligent robots that can interact socially with humans and provide customized services to individuals (Breazeal, 2003; You & Cho, 2018: Lee & Park, 2021). As cutting-edge technologies that form the basis of social robots, such as the Internet of Things (IoT), Big Data, and

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AI, develop, public expectations for the spread of social robots are also rising (Lee et al., 2019). However, a paradigm shift is needed for social robots to settle into our society and life fully. A machine-centered approach has dominated the conventional view of social robots. Under the machine-centered approach, we emphasize the performance advantage of innovative products, ideas, and technologies (De Santis et al., 2008; Shin, 2014). This approach needs to be revised to understand the needs of consumers and design the features and products that consumers need.

For social robots to be well accepted into human life, manufacturers and researchers must recognize and explore the importance of a human-centered design paradigm that considers emotions (Norman, 2013; Duffy, 2016; Hoffman, 2023). Many products consumers favor in the market have been developed under a human-centered perspective and approach (Bannon, 2011; Shiizuka & Hashizume, 2011). The human-centered approach is multidisciplinary research focused on developing consumer-friendly and intuitively usable products to meet humans' essential needs and expectations (Shiizuka & Hashizume, 2011; Jaimes et al., 2006). Human Factor and Kansei Engineering are closely related to human-centered approaches (Sun et al., 2019).

In this study, we try to identify consumer emotions on the appearance of social robots, focusing on the Kansei engineering perspective, which is one of the human-centered approaches. Consumer and user emotions affect the consumer's perception, inference, evaluation, and expectation formation for a product and can further influence the consumer's attitude and product performance inference (Westbrook & Oliver, 1991; Chaudhuri, 2006; Nagamachi, 2011). In order for humans to accept and trust social robots in their daily lives, it is necessary to consider both the technical implementation and psychological aspects of social robots. In particular, the emotions consumers/users feel about the appearance of social robots are essential because they can affect individual perceptions and expectations of social robots in social robot-human interactions.

This study aims to understand the emotions consumers feel according to the appearance design of social robots and to derive clusters of social robots with similar characteristics based on consumer emotions. Furthermore, we will confirm each derived social robot cluster's essential characteristics and compare the clusters' differences.

In order to achieve the purpose of this study, we will measure consumer emotion on the appearance of social robots using the semantic differential method (Taherdoost, 2019). First, we will measure consumers' emotions about social robots with different appearance designs through Kansei words and analyze consumer emotions to derive major consumer emotion factors. Then, based on the derived major consumer emotion factors, we will cluster social robots through multidimensional scaling (MDS) and K-means cluster analysis. Through this, we will identify the characteristics of each social robot cluster, and the differences in consumer emotion will be compared and analyzed.

2. Research Design

2.1. Measurements

In order to evaluate consumer emotions according to the appearance design of social robots, robot data with different designs were collected from the ABOT Database (Phillips et al., 2018; Ha et al., 2021). The ABOT Database is an open data set that provides information such as product names, images, and human similarity scores for about 250 robots, including actual commercialized robots and robots developed for exhibition and research purposes to support research and development related to robot design. First, we collected basic information and pictures for 45 robots in the ABOT Database. Then, we evaluated the designs of the collected robots according to the presence or absence of 18 physical components (e.g., arms, heads, legs, eyebrows, Etc.). Afterward, through a pilot test, four experiment participants were asked to select a robot that could easily interact with humans and were expected to have a high commercialization potential. The 30 robots to be finally used in the experiment are shown in <Figure 1>.

Next, we built a framework to measure the emotions consumers feel when they see the appearance design of social robots. We used three channels to establish a framework for measuring emotion:

1. Existing studies and literature related to social robot design emotion
2. Keywords derived from SNS and product reviews related to social robot products
3. Qualitative interviews on social robot design

Through this, Kansei words were collected and integrated. The Kansei words collected and integrated are shown in <Table 1>. Afterward, experts in social robots and design determined the importance of the collected words. Finally, we established a social robot emotional framework by selecting 21 Kansei words. The framework finally selected and built is summarized in <Table 2>. Based on the established framework, consumer emotions for 30 robots were measured.

2.2. Procedure

For this study, we conducted a survey targeting

〈Figure 1〉 Social robot image for research

〈Table 1〉 Kansei words of Social robot

Research (year)	Kansei words
Massimiliano et al. (2005)	Interesting, lively, amusing, dynamic, stimulating, pleasant, useful, relaxing, worrying, scary, depressing, dangerous, out of control, embarrassing, overwhelming
Hwang et al. (2013)	Sociable, outgoing, confident, friendly, nice, pleasant, helpful, hardworking, emotionally stable, adjusted, intelligent, imaginative, flexible
Osawa and Imai (2010)	Formal-informal, Flexible-inflexible, New-old, Gentle- horrible, Interesting-uninteresting, Hot-cold Intimate-not intimate, Pleasant-unpleasant, Lively- gloomy, Wise-foolish, Showy-plain, Fast-slow Unselfish-selfish, Simple-complex, Understandable-difficult to understand, Strong-weak, Queer-cool
Kuhnert et al. (2017)	Friendly-unfriendly, functional-human, strong-weak, active-passive, cautious-incautious, soft-wild, honest-dishonest, lazy-hardworking, untrustworthy-trustworthy, aggressive-gentle, cunning-sincere, nice-bad, selfish-selfless, likable-unlikable, stupid-intelligent, reliable-unreliable, feminine-masculine, alive-dead, certain-uncertain, extroverted-introverted, peaceful-quarrelsome, incompetent-competent, happy-sad, determining-reserved, reckless-helpful, rational-emotional, sensitive-cool, inferior-superior,

〈Table 2〉 Kansei words of Social robot for research

Pairs of Kansei words included in the research
classic (Traditional)-modern (High-Tech), inflexible (rigid)–flexible, conservative–progressive, Stupid–Smart, disconnected–connected, crude-elaborate (delicate), inorganic–Organic, unfriendly–friendly, Unnatural–Natural, common (nonspecific)-Unique (specific), stereotypical–unprecedented, open-closed, common (popular)-uncommon (unpopular), monotonous–varied, simple-complicated (complex), Static–Dynamic, Inactive (Passive)-Active (Dynamic), introverted-extroverted, feminine–masculine, weak–strong, warm-cold

online panels of 20~40-year-old from a research company in South Korea. Participants were randomly assigned 1-3 robots from a pool of 30 robots used in the experiment. Participants evaluated the emotions they felt towards the appearance of the assigned social robot using a semantic differential scale composed of 21 Kansei words. We measured each item of Kansei words on a 7-point Likert scale of polarity, and the survey took approximately 15 minutes per participant.

2.3. Participants

A total of 520 participants responded to the survey, and we used the responses of 465 participants who completed the survey and provided reliable answers. The age distribution of the respondents was 155 (33.99%) in their 20s, 154 (33.77%) in their 30s, and 156 (34.21%) in their 40s. The gender distribution was pretty even, with 230 (52.63%) male and 235 (51.53%) female participants.

2.4. Factor Analysis on Social Robot Appearance Design Emotion

A factor analysis using varimax rotation was conducted on 21 Kansei words to identify the key emotional factors from consumer emotion towards the appearance design of collected social robots. The Bartlett’s sphericity test showed a significant correlation between variables (p<0.001), and the Kaiser-Meyer-Olkin (KMO) value, indicating the fitness of the factor analysis model, was 0.903. Five emotional factors were extracted based on an eigenvalue of 1, which explained 67.2% of the total variance. The primary consumer emotional factors were named “High-Tech”, “Animacy”, “Unique”, “Kinesthesia”, and “Strong”, each of which was assigned emotional words and loading values, summarized in <Table 3>.

2.5. Analysis

We calculated the factor scores for each of the five emotional factors for the 30 robots used in the experiment. We used these factor scores to obtain MDS coordinates, placing the robots in a two-dimensional space. We then performed cluster analysis on the robots using the K-means algorithm based on their coordinate values.

3. Research Results

3.1. Overall Consumer Emotional Evaluation of the Social Robots’ Appearance

Descriptive statistical analysis was conducted for

〈Table 3〉 Factor analysis of Kansei words

Variable		Factor loading	Cronbach’s α
Factor 1 (High-Tech)	stupid-smart	0.789	0.877
	inflexible-flexible	0.717	
	conservative-progressive	0.696	
	closed-open	0.669	
	disconnected-connected	0.664	
	classic-modern	0.597	
Factor 2 (Animacy)	unnatural-natural	0.827	0.839
	inorganic-organic	0.759	
	unfriendly-friendly	0.741	
	crude-delicate	0.704	
Factor 3 (Unique)	nonspecific-specific	0.785	0.780
	stereotypical-unprecedented	0.769	
	monotonous-varied	0.605	
	simple-complex	0.555	
	common-uncommon	0.535	
Factor 4 (Kinesthesia)	static-dynamic	0.734	0.814
	passive-active	0.729	
	introverted-extroverted	0.623	
Factor 5 (Strong)	weak-strong	0.745	0.646
	feminine-masculine	0.734	

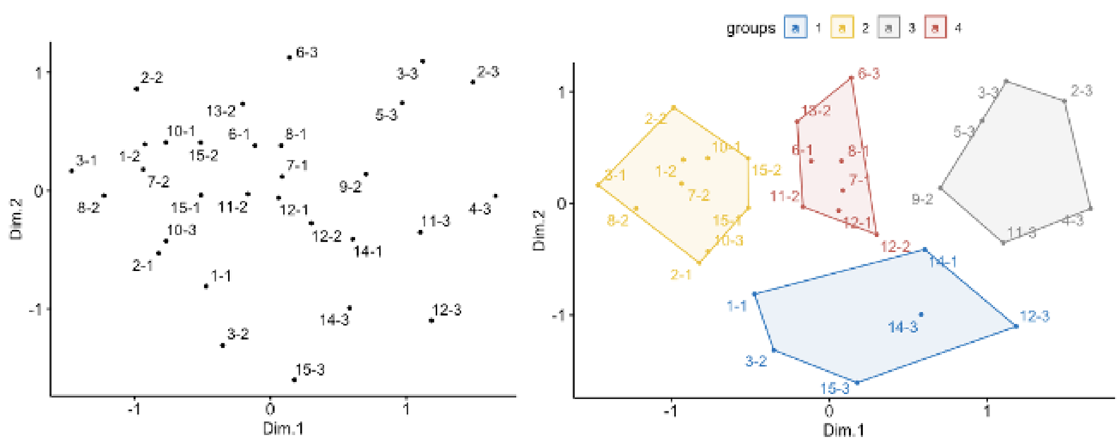
each emotional factor to examine the overall consumer emotional evaluation of the 30 social robot designs used in the experiment. The results are shown in <Table 4>. On average, the "High-Tech" emotional factor had the highest score, followed by "Kinesthesia" and "Animacy" emotional factors. The lowest of the significant consumer emotional factors was the "Unique" emotional factor.

3.2. Clusters of Social Robots and Characteristics of Each Cluster

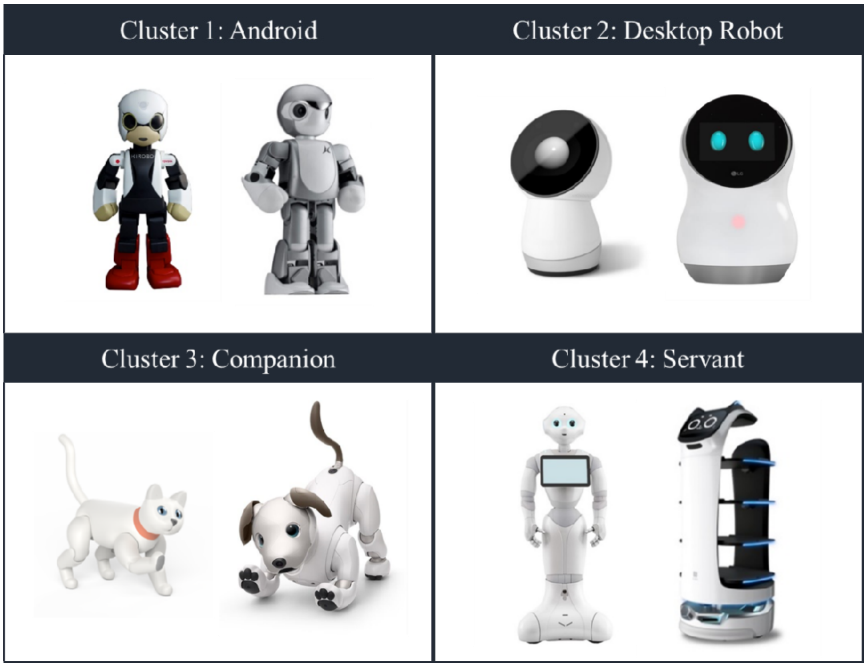
To visually observe the similarity among the social robots based on their 5-factor scores, multidimensional scaling (MDS) was used. MDS is a statistical technique that represents objects as points in a two-dimensional virtual space, making it easy to confirm the proximity between objects (Eom, 2009). In this study, the horizontal axis of the virtual space was composed of the degree to which the robot can display various movements, i.e., the diversity of robot movements, and the vertical axis was composed of the degree to which the robot's appearance is similar to that of humans. Based on the position of each social robot in the virtual space, K-means clustering analysis was conducted, resulting in a total of 4 clusters. The result of the K-means clustering analysis using MDS is shown in <Figure 2>.

〈Table 4〉 Description by Consumer Kansei

Factor	Min	Max	Mean	SD
Factor 1 (High-Tech)	3.683	5.161	4.387	0.359
Factor 2 (Animacy)	2.850	5.742	3.961	0.635
Factor 3 (Unique)	2.967	4.525	3.649	0.370
Factor 4 (Kinesthesia)	3.086	5.467	4.284	0.657
Factor 5 (Strong)	2.798	4.925	3.954	0.546



〈Figure 2〉 Results of MDS and K-means clustering



〈Figure 3〉 Representative robots by cluster

The nomenclature and representative characteristics of each cluster are as follows:

Cluster 1(Android): This represents the typical robot image consumers easily recall when thinking of robots. It has a strong appearance and a cold, masculine look and is equipped with facial features evenly distributed for making expressions.

Cluster 2(Desktop Robot): Has a similar appearance to portable household robots that are currently widely installed in homes. It often lacks clear articulation or visible actuator elements, which may lead to lower expectations for its verbal and nonverbal interaction abilities, similar to installation robots.

Cluster 3(Companion): Has an overall shape that resembles animals, with a significant emphasis on joints that can perform three-dimensional movements.

Cluster 4(Servant): Has a mechanical appearance typical of service robots used for various purposes such as serving and guiding. It often features a screen and combines human facial features such as eyes and mouths with its mechanical appearance.

3.3. Comparative Analysis of Clusters based on Emotional Factors

We compared and analyzed the derived social robot clusters using emotional factors. The average of the emotional factors for the appearance of social robots in each cluster was compared. As a result, the ‘High-Tech (H-T)’ and ‘Animacy’ emotional factors were the highest in cluster 3. The ‘Unique’ and ‘Kinesthesia’, ‘Strong’ emotional factors were the highest in cluster 1. In contrast, the ‘High-Tech (H-T)’, ‘Animacy’, ‘Unique’, and

〈Table 5〉 Descriptive statistics on the physical components of robots

Variable		Cluster 1 Android (n = 6)	Cluster 2 Desktop Robot (n = 10)	Cluster 3 Companion (n = 6)	Cluster 4 Servant (n = 8)
Presence or Absence of Body Parts	Head	100.00% (6)	80.00% (8)	100.00% (6)	100.00% (8)
	Eyes	83.33% (5)	90.00% (9)	100.00% (6)	100.00% (8)
	Nose	50.00% (3)	10.00% (1)	83.33% (5)	37.50% (3)
	Mouth	66.67% (4)	50.00% (5)	83.33% (5)	87.50% (7)
	Ears	50.00% (3)	40.00% (4)	66.67% (4)	37.50% (3)
	Neck	66.67% (4)	40.00% (4)	66.67% (4)	62.50% (5)
	Tail	33.33% (2)	0% (0)	83.33% (5)	12.50% (1)
Average Number of Body Parts	Arm	1	1	0	1
	Leg	1.66	0.80	3	1.25
Style	Human-like	50.00% (3)	60.00% (6)	0% (0)	50.00% (4)
	Animal-like	33.33% (2)	10.00% (1)	83.33% (5)	37.50% (3)
	Machine-like	16.77% (1)	30.00% (3)	16.77% (1)	12.50% (1)

'Kinesthesia' emotional factors were the lowest in cluster 2, and the 'Strong' emotional factor was the lowest in cluster 3. The average values of emotional factors by cluster are shown in <Table 6>. The distribution of emotional factors for each cluster is summarized in a radar chart as shown in <Figure 4>.

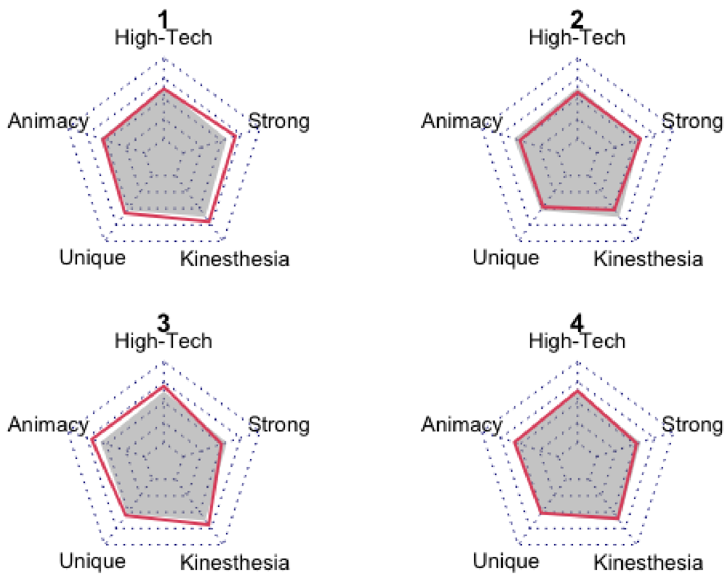
3.4. The Effect of Consumer Kansei on Consumer Attitude

In this part, we investigated how consumers' five main Kansei toward social robots affect consumers' attitudes. First, consumer attitudes were analyzed based on their effect, usefulness, and usability ratings of social robots. Multiple regression analysis was then conducted to examine the impact of each main affective response on attitudes, with the consumers' five main Kansei as independent variables and consumer attitudes as the dependent variable. The results revealed that two of the consumers' five main Kansei, Factor 1 (High-Tech) and Factor 2 (Animacy), significantly influenced consumer attitudes toward social robots (Table 7).

First, the 'High-Tech' emotion represents a feeling of being smart, open-minded, and flexible in behavior. This suggests that if social robots provide information in a slightly smarter way or show flexible behavior, people are more likely to evaluate them positively. Next, the 'Animacy' emotion refers to the degree to which robots behave organically and have high activity. The more organic and responsive robots are in human actions and speech, the more positive the consumer's attitude toward them can be.

〈Table 6〉 Mean of Consumer Kansei by cluster

Cluster	H-T	Animacy	Unique	Kinesthesia	Strong
1(Android)	4.346	3.795	3.997	4.898	4.773
2(Desktop Robot)	4.047	3.508	3.343	3.646	3.977
3(Companion)	4.878	4.830	3.868	4.846	3.513
4(Servant)	4.475	4.001	3.607	4.199	3.642



〈Figure 4〉 Radar chart by cluster

4. Discussion

This study examines consumer emotions on the appearance design of social robots, derives potential clusters of social robots based on consumer emotions, and compares and analyzes the differences in distinctive characteristics of each cluster. First, this study identified the emotions consumers felt about social robot appearance design using Kansei words with a Kansei engineering approach and identified five emotional factors that play an essential role in consumer perception and evaluation of social robots through factor analysis. Second, based on the derived emotional factors, we tried to derive potential clusters of social robots using multidimensional scaling and the K-means algorithm. As a result, four different robot clusters were derived. Lastly, we compared and analyzed each robot group's appearance characteristics and emotional differences derived through the emotional factor.

Cluster 1(Android) has human characteristics such as arms, legs, and facial expressions and can

〈Table 7〉 The Effect of Consumer Kansei on Consumer Attitude

Dependent variable	Independent variable	Unstandardized coefficients		Standardized coefficients	t(p)	Collinearity diagnostics	
		B	SE	β		TOL	VIF
Consumer Attitude	**Factor 1 (High-Tech)**	**0.590**	**0.037**	**0.477**	**15.830*****	**0.450**	**2.22**
	Factor 2 (Animacy)	**0.295**	**0.024**	**0.296**	**11.871*****	**0.657**	**1.52**
	Factor 3 (Unique)	0.001	0.033	0.007	0.302	0.666	1.50
	Factor 4 (Kinesthesia)	-0.058	0.030	-0.054	-1.907	0.509	1.97
	Factor 5 (Strong)	-0.013	0.029	-0.010	-0.475	0.842	1.19
F(p)	212.000***						
Adj. R^2	0.433						
Durbin-Watson	1.71***						

be inferred as a set of robots that represent a typical image (Stereotype) shared by many consumers about humanoid robots. In Cluster 1, the values of the ‘Kinesthesia’ and ‘Strong’ factors were high, while the value of the ‘Animacy’ factor was low. The robot included in Cluster 1 has a human shape, giving an active and strong feeling, but it is not easy to recognize it as an organic life form (animacy). When designing and developing the form of social robots, focusing solely on realizing the typical image of robots could imply a disconnect from the emotions necessary for social robots to interact with humans in a warm and friendly manner.

Cluster 2(Desktop Robot) often exhibits a form of portable robots that are easily managed in homes, such as designed AI speakers, and often includes visual elements such as eyes for nonverbal interaction. The robots in Cluster 2 showed high values for the ‘High-Tech’ and ‘Strong’ factors but low values for the ‘Animacy’ and ‘Unique’ factors. In addition, cluster 2 had generally lower values for all emotional factors than other clusters. Cluster 2 appears to be a collection of social robots with simplistic forms capable of serving as a consumer’s assistant through voice-based interactions rather than gesture-based language. The robots included in Cluster 2 are well-suited to the advanced and strong image (‘High-Tech’, ‘Strong’) that people expect from robot assistants. However, because they adopt a simple design to avoid giving consumers a sense of aversion, they may not convey a sense of being alive or unique (‘Animacy’, ‘Unique’).

Cluster 3(Companion) stands out from other clusters in that it consists of companion robots with animal-like forms. Cluster 3 showed the highest value for the ‘High-Tech’ factor, followed by ‘Kinesthesia’ and ‘Animacy’, while the ‘Strong’ factor, representing the robustness and strength of the robot, received a relatively low score. In Cluster 3, the ‘High-Tech’, ‘Animacy’, and ‘Kinesthesia’ factors were highly evaluated compared to other clusters. It can be inferred that when consumers evaluate the robots included in Cluster 3, they associate them with organic and active images of actual companion animals. Therefore, the importance of considering organic features and active elements similar to real companion animals in the design and development of companion robots can be confirmed.

Unlike the previously observed Clusters 1-3, which were more suitable for home environments, the robots in Cluster 4(Servant) were observed to possess a form suitable for service environments. Their main features include being relatively large in size, having limited physical elements (such as eyes) for nonverbal communication with humans, and possessing mechanical elements like screens that make it easier to interact with them for service provision. In Cluster 4, the values of ‘High-Tech’ factor were high, and the value of ‘Animacy’ and ‘Unique’ factor was low. The overall high consumer emotion within Cluster 4 is the ‘High-Tech’ factor, while the lowest emotion is the ‘Unique’ factor. Compared to other clusters, all consumer emotions except for ‘Strong’ were low. This can be inferred from the fact that consumers expect advanced functionality for successful task completion and differentiated service provision from service robots. We anticipate that consumers will prioritize the functionality of service robots in effectively performing intended tasks to achieve their goals, rather than focusing on human-robot interaction or the unique emotions that robots can evoke. Therefore, it seems important to consider the design development that highlights the performance capability (Competence) of service robots.

5. Conclusion

In summary, from the above discussion, it can be concluded that the appearance design of social robots can evoke various emotions in consumers, and there is a need for different design and development strategies for social robots depending on the emotions stimulated by the robot design. This conclusion emphasizes the need to understand consumers’ emotions when they see social robots and reflect them in the design for stakeholders who develop social robots, such as developers and designers. Interactions between humans and robots are continuously increasing, and robots are entering more deeply into daily life. Therefore, stakeholders will be able to induce or minimize specific emotions considering the purpose of development or the usage environment of consumers. For example, it can be effective to apply a design considering emotions that can stimulate curiosity or interest in a social robot expected to be used by young children so that using the robot is a fun and exciting experience. Alternatively, for social robots developed to help users with tasks, it may be essential to make them feel a sense of stability and safety in the process of robot operation. To this end, stakeholders must develop robots with design elements showing predictable movements or progress. As such, the design of the robot must be developed differently depending on the purpose of the use or the usage environment of the consumer, and at this time, the emotions consumers can feel are diverse. The emotional elements of this study and the characteristics of the derived clusters can serve as a reference for interested parties to understand consumers' emotions and reflect them to determine which elements should be applied in terms of design.

This research has several contributions. First, this study makes a theoretical contribution by establishing a Kansei engineering approach to understand social robots, as opposed to a machine-centered approach. To evaluate consumer emotions towards social robot appearance, this study constructed a social robot design emotion framework based on a semantic differential method, and identified five important factors of emotions on social robot appearance based on the measured emotions. This development goes beyond the existing paradigm of evaluating social robots from a mechanical perspective, such as physical components and embedded functions, and creates a system to understand and evaluate social robots from a consumer's emotional perspective.

Second, This study is significant in identifying key variables that affect consumer attitudes and satisfaction among various consumer emotions elicited by the appearance of social robots. According to this study, among various consumer emotions elicited by the appearance of social robots, "High-Tech" and "Animacy" factors have significantly impacted consumer attitudes toward social robots. Research exploring how consumer emotions towards social robots can lead to consumer satisfaction or market success is limited. Our study provides an academic contribution to robot research by comprehensively analyzing the emotions evoked by design elements of social robots and their impact on consumer attitudes.

Third, this study is meaningful in that it derives four potential robot clusters based on consumer emotions and interprets the meaning of each cluster. It is interesting to reveal how different robots with various designs and characteristics are categorized in consumers' minds. This study extracted four robot clusters based on consumers' emotional responses to robot appearances and provides insights into what consumers expect from robots through discussions of each cluster. This study has practical implications for practitioners involved in the design and development of social robots, as it offers fundamental data to establish an effective robot design strategy that aligns with the target market.

Lastly, the emotional factors in social robot design developed in this study can be utilized as variables for predicting the marketability and potential customers of newly developed social robots. While not investigated in this study, future research could explore how the physical elements of a robot's design (such as arms, head, legs, eyebrows, etc.) affect the five emotional factors identified in this study. Based on such analyses, the emotional responses or expectations that newly developed robots may elicit from consumers can be predicted in advance, and the predicted results can be utilized as the basis for selecting target markets and establishing marketing strategies.

Despite the contributions of this study, there are some limitations that should be noted. Firstly, this study has a limitation in that it only analyzed a limited selection of 30 social robots, and to generalize and extend the research findings, it is necessary to consider a wider variety of robot designs that were not examined in this study. Secondly, this study measured consumer emotions through the static image of a robot, which limits its ability to consider emotions that occur in the physical interaction context between humans and robots, such as conversation or movement. Thirdly, the emotions of consumers towards social robots may vary depending on personal traits, environment, background, and even the purpose and usage context of the robot. However, these factors were not taken into consideration in this study. In future research, it will be necessary to comprehensively consider consumers' emotions towards social robots, individual personality traits, and the context in which individuals interact with social robots. Additionally, in this study, we investigated the impact of emotions derived from the appearance of social robots on consumer attitudes. Furthermore, in future research, based on empirical data, we plan to analyze the impact of the design elements and emotional factors of social robots presented in this study on actual consumer reactions, such as sales volume and customer ratings.

References

Bannon, L. (2011) Reimagining HCI: toward a more human-centered perspective. *Interactions*, 18 (4), 50-57.

Breazeal, C. (2003). Emotion and sociable humanoid robots. *International journal of human-computer studies*, 59 (1-2), 119-155.

Chaudhuri, A. (2006). *Emotion and reason in consumer behavior*. Oxfordshire, UK: Routledge.

De Santis, A., Siciliano, B., De Luca, A., & Bicchi, A. (2008). An atlas of physical human–robot interaction. *Mechanism and Machine Theory*, 43(3), 253-270.

Duffy, V. G. (2016). Modern human-robot interaction in smart services and value co-creation. In International Conference on Digital Human Modeling and Applications in Health, Safety, Ergonomics and Risk Management, Toronto, ON, Canada.

Eom, S. (2009). *Author Cocitation Analysis: Quantitative Methods for Mapping the Intellectual Structure of an Academic Discipline*. PA, USA: IGI Global.

Ha, S., Lee, J., Yoo, I. J., & Park, D. H. (2021). Different Look, Different Feel: Social Robot Design Evaluation Model Based on ABOT Attributes and Consumer Emotions. *Journal of Intelligence and Information Systems*, 27(2), 55-78.

Hoffman, G. (2019). Anki, Jibo, and Kuri: What we can learn from social robots that didn't make it. IEEE Spectrum. https://spectrum.ieee.org/anki-jibo-and-kuri-what-we-can-learn-from-social-robotics-failures

Hwang, J., Park, T., & Hwang, W. (2013). The effects of overall robot shape on the emotions invoked in users and the perceived personalities of robot. *Applied ergonomics*, 44 (3), 459-471.

Jaimes, A., Sebe, N., & Gatica-Perez, D. (2006). Human-centered computing: a multimedia perspective. In Proceedings of the 14th ACM international conference on Multimedia, Santa Barbara, CA, USA.

Kuhnert, B., Ragni, M., & Lindner, F. (2017). The gap between human's attitude towards robots in general and human's expectation of an ideal everyday life robot. In 2017 26th IEEE international symposium on robot and human interactive communication (RO-MAN), Lisbon, Portugal.

Lee, J., & Park, D. H. (2021). Are you a Machine or Human?: The Effects of Human-likeness on Consumer Anthropomorphism Depending on Construal Level. *Journal of Intelligence and Information Systems*, 27(1), 129-149.

Lee, J., Yoo, I. J., & Park, D. H. (2019). Implementation strategy for the elderly care solution based on usage log analysis: focusing on the case of Hyodol product. *Journal of Intelligence and Information Systems*, 25(3), 117-140.

Massimiliano, S., Maria, V. G., & Ferdinando, F. (2005). Robots in a domestic setting: a psychological approach. *Universal Access in the Information Society*, 4(2), 146-155.

Nagamachi, M. (2011). *Kansei/affective engineering*. Boca Raton, FL, USA: CRC press.

Norman, D. (2013). *The Design of Everyday Things*. NY, USA: Basic Books.

Osawa, H., & Imai, M. (2010). *Interaction between a Human and an Anthropomorphized Object*. London, UK: IntechOpen.

Phillips, E., Zhao, X., Ullman, D., & Malle, B. F. (2018). What is human-like? decomposing robots' human-like appearance using the anthropomorphic robot (abot) database. In Proceedings of the 2018 ACM/IEEE international conference on human-robot interaction, Chicago, IL, USA.

Shiizuka, H., & Hashizume, A. (2011). The role of kansei/affective engineering and its expected in aging society. In Intelligent Decision Technologies: Proceedings of the 3rd International Conference on Intelligent Decision Technologies (IDT'2011), Berlin, Heidelberg, Germany.

Shin, D.-J. (2014). Human Robot Interaction: ICRA 2014 Research Trend. *Korea robotics society review, 11(4), 29-35.*

Sun, X., Houssin, R., Renaud, J., & Gardoni, M. (2019). A review of methodologies for integrating human factors and ergonomics in engineering design. *International Journal of Production Research*, 57 (15-16), 4961-4976.

Taherdoost, H. (2019). What is the best response scale for survey and questionnaire design; review of different lengths of rating scale/attitude scale/Likert scale. *Hamed Taherdoost*, 1-10.

Westbrook, R. A., & Oliver, R. L. (1991). The dimensionality of consumption emotion patterns and consumer satisfaction. *Journal of consumer research*, 18(1), 84-91.

You, E. S., & Cho, M. R. (2018). The ethics of robots and humans in the post-human age. *The Journal of the Korea Contents Association*, 18(3), 592-600.

국문요약

소셜 로봇 외형 디자인에 대한 소비자 감성에 관한 연구: 다차원 척도법 (MDS)과 군집분석을 중심으로

유성훈* · 윤지찬* · 이준식* · 박도형**

소셜 로봇이 인간의 일상생활에 자리매김하기 위해서는 소셜 로봇의 기술적 구현과 소셜 로봇을 바라보는 인간의 심리를 함께 고려하는 것이 중요하다. 본 연구는 소셜 로봇의 외형 디자인에 대해 소비자가 느끼는 감성에 기반하여 잠재적인 소셜 로봇 군집을 도출하고, 각 군집이 갖는 중요한 디자인적 특징 및 감성 차이를 식별 및 비교하고자 하였다. 소셜 로봇에 대해 소비자가 느끼는 감성을 측정 및 평가하기 위한 소셜 로봇 감성 프레임워크를 구축하고, 감성공학적 접근방법인 의미분별척도법에 기반해 소셜 로봇 디자인 감성을 평가하였다. 감성 평가 결과를 토대로 다차원 척도법과 K-means 군집분석을 실시하여 30개의 소셜 로봇을 4개의 군집으로 분류하였으며, 각 군집 별 디자인 요소의 특징을 확인하고, 소비자 감성을 비교 분석하였다. 각 군집 별로 도출된 디자인적 특징 및 감성 차이를 바탕으로 인간중심적 관점에서 성공적인 소셜 로봇 디자인 및 개발을 위한 전략적 방향을 제언하였다.

주제어 : 소셜 로봇, 소셜 로봇 외형, 감성공학, 의미분별척도법

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저 자 소 개

유성훈
제주대학교 전산통계학과에서 이학 학사를 취득하였으며, 국민대학교 비즈니스IT전문대학원에서 석사과정 재학 중이다. 주요 연구분야는 사용자/고객 행동, 고객 애널리틱스, 고객경험 등과 관련된 연구를 수행하고 있다.

윤지찬
국민대학교 경영정보학부에서 경영학사 및 공학사를 취득하였으며, 국민대학교 비즈니스IT전문대학원에서 석사과정에 재학 중이다. 주요 연구분야는 디지털 에이전트, 데이터 기반 사용자/소비자 고객 행동 분석, 고객 경험 디자인 등과 관련된 연구를 수행하고 있다.

이준식
국민대학교 경영대학 경영정보 심화전공, EmTeD (Emerging Technology Beyond Design; 미래기술융합디자인) 부전공으로 학사 학위, 동 대학 비즈니스IT전문대학원에서 공학석사 학위를 취득하였으며, 현재 동 대학원 CX트랙 박사과정에 재학 중이다. 주요 연구분야는 사회심리학 기반 사용자/소비자 행동 이론 (User/Customer Behavior), 통계 및 인공지능 기법 기반의 사용자/소비자 애널리틱스 (User/Customer Analytics), 디자인사고 기반의 사용자/소비자 경험 디자인 (Experience Design)이며, Data-Driven UX 개발, 온라인 소비자 데이터 분석 기반의 고객전략 수립, 소비자 감성 기반 디자인평가 등의 연구를 수행하고 있다.

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.