Designing Healthcare Robots at Home for Older Adults: A Kano Model Perspective

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ABSTRACT

Healthcare robots at home are increasingly essential for promoting the independence of older adults, yet their widespread acceptance is hindered by a lack of clarity regarding optimal design features. To address this, this study employs the Kano model to systematically identify and prioritize the features of healthcare robots that most significantly influence user satisfaction and acceptance among older adults. We conducted a survey study with 253 U.S. older adults to evaluate a variety of robot features. The results highlight design features that markedly affect user satisfaction and acceptance. 'Medication Management' and 'Managing Illness and Monitoring Health' are identified as one-dimensional features, whereas 'Animal-like Appearance' is a less favored reverse feature, potentially diminishing satisfaction. 'Housework' along with seven other features, is recognized as attractive, with sixteen features deemed indifferent.

CCS CONCEPTS

• **Human-centered computing → User studies**; • **Computer systems organization → Robotics**; • **Social and professional topics → Seniors**.

KEYWORDS

healthcare robot, older adults, kano model, satisfaction, acceptance

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1 INTRODUCTION

The demographic landscape of the United States has undergone a significant shift over the last century. From 1920 to 2020, the population of Americans aged 65 and older has grown almost five times, outpacing the increase in the total population [7]. The 2020 Census underscores this shift, revealing that one in six Americans now belongs to this age group [7]. Accompanying this change in age demographics is a rise in chronic health issues, necessitating an expanded range of healthcare services [3, 6, 13].

In this evolving landscape, healthcare robots at home have become increasingly important [1, 25, 28, 36]. These robots are tailored to enhance the health and lifestyle of older adults by providing vital health-related services, supporting their desire to age in place - that is, to continue living in their own homes for as long as possible [8, 25]. Healthcare robots offer a spectrum of assistance, ranging from tasks that promote independence to those requiring cognitive engagement and social interaction [28]. For instance, Home Exploring Robot Butler, short for HERB, is specifically designed to assist the elderly and those with disabilities in maintaining their independence by carrying out household tasks [19].

Despite their potential, the acceptance of healthcare robots at home remains a significant challenge. Research in this field has been extensive, focusing on identifying the factors that influence acceptance [9, 11, 14, 20]. This includes aspects of robot aesthetic design features such as appearance [2, 15], and functionalities like mobility assistance [3, 6, 10, 13, 27]. However, there remains a gap in understanding which features are most critical in gaining acceptance among older adults, leaving developers without specific guidance on feature prioritization.

The Kano model, pivotal for feature assessment and prioritization, categorizes consumer preferences into five groups. This classification clarifies the interplay between product features and user satisfaction and acceptance [12, 16, 22]. As shown in Figure 1, the categories include: Must-be features, such as a smartphone's ability to make and receive calls, which are essential. Their absence causes dissatisfaction, but their presence doesn't significantly increase satisfaction. One-dimensional features, such as phone processing speed, directly influence satisfaction. Feedback for these attributes is usually positive when met and negative when unmet. Attractive features, like face recognition, greatly enhance satisfaction but are tolerable if absent. Indifferent features, such as the internal location of the chip, have little to no impact on user satisfaction.

Finally, reverse features, like unwanted mandatory services, create dissatisfaction when present. These categories aid in prioritizing features based on their impact on user acceptance and satisfaction. The Kano model has been applied in product and service design [5, 17, 26, 29, 30, 32–34]. Its widespread use underscores its importance in informing the design and strategic development of healthcare robots, ensuring alignment with user expectations and needs.

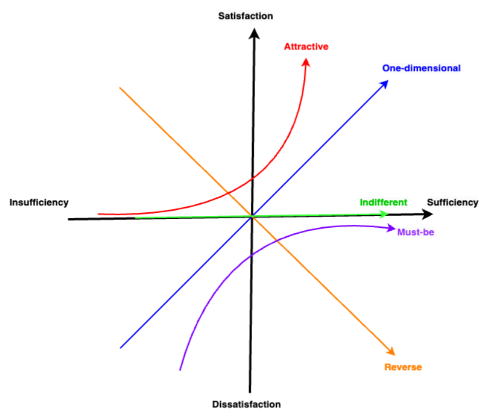

Figure 1: Kano model of customer satisfaction [12].

This research aims to expand the understanding of the features currently found in healthcare robots designed for seniors, with a focus on methodically organizing and prioritizing their needs and preferences. We first identified the range of features of healthcare robots from existing literature, followed by the development of a two-dimensional survey grounded in the Kano model's framework. This survey was then administered to a cohort of 253 older adults in the United States. Employing the Kano model, we categorized the features of healthcare robots and assessed the corresponding levels of consumer satisfaction and dissatisfaction. For instance, animal-like appearances, categorized as 'reverse' features, negatively affect user satisfaction, suggesting their exclusion from design. Conversely, critical 'one-dimensional' features like 'Medication Management' and 'Managing Illness and Monitoring Health' significantly enhance user satisfaction and acceptance, emphasizing their importance in design considerations.

This study makes several key contributions. First, it sheds light on the differing levels of importance that various healthcare robot features hold in meeting the needs and preferences of older adults. Second, it identifies a clear link between the integration of certain features and the levels of satisfaction and acceptance these features garner from users. Finally, it offers practical design insights that could significantly improve the acceptance and effectiveness of healthcare robots for older adults.

2 METHOD

2.1 Participants

This study recruited 253 older adults in the U.S. via the Qualtrics survey platform, using CloudResearch's participant pool. All participants were over 64, with an average age of 69.46 years (standard deviation = 3.96). Our sample was gender-balanced, comprising 140 women and 113 men. To ensure data reliability, we included three attention-check questions in the survey. We also screened for eligibility based on age and absence of visual impairments that could interfere with survey participation. The survey took 20-25 minutes to complete, and participants were compensated $5 for their contribution. Before collecting data, we secured an exemption from ongoing review by the University's Institutional Review Board (IRB). Informed consent was obtained from all participants.

2.2 Study Design

Our study was grounded in the Kano model to categorize and prioritize healthcare robot features for older adults. We followed a three-step methodology: first, identifying relevant healthcare robot features through literature review; second, developing and distributing a Kano-based questionnaire; and third, analyzing the data according to the Kano model's criteria.

2.2.1 Healthcare robot feature selection. We conducted a literature review to create a list of healthcare robot features designed for older adults. We focused on literature review articles summarizing the acceptance of healthcare robots by this demographic. To achieve this, search terms including "robot", "healthcare", "older", "acceptance", and "review" were used in databases including IEEE Xplore and Google Scholar. We focused on how different features, from functional ones providing assistance to characteristics enhancing human-robot interactions, influence user acceptance. The outcome of this extensive review is the identification of 27 distinct features pertinent to healthcare robots for older adults [3, 6, 13, 21, 27, 35]. These features are detailed in Table 2.

2.2.2 Questionnaire design. The questionnaire was organized in two sections. In the first section, we utilized a Kano-style questionnaire, focusing on the 27 identified features. Participants were asked to consider both the functional (presence) and dysfunctional (absence) aspects of each feature. For example, they would respond to a functional question like, "If you have a healthcare robot that can assist with preparing meals, how do you feel?" and a corresponding dysfunctional question, "If you have a healthcare robot that cannot assist with preparing meals, how do you feel?" with options including 'I like it', 'I expect it', 'I'm neutral', 'I can tolerate it', and 'I dislike it'. Additionally, the questionnaire contained a self-stated importance partto further determine the significance of these features for the participants [4, 18]. They rated each feature on a 5-point scale, from 'Very important' to 'Not important at all'. An illustrative question in this part was, "How important is it for you to have a healthcare robot that can assist with preparing meals?"

The second section of the questionnaire collects demographic data, focusing on the participants' age and gender. The questionnaire was distributed on Qualtrics survey platform, facilitating easy access for participants to provide their responses.

2.2.3 Data analysis. The Kano questionnaire analysis categorized each feature into Kano model categories: M, O, A, I, R, and an additional category for Questionable (Q) responses, which indicates contradictions in answers. The categorization followed the Kano model's established evaluation criteria, as illustrated in Table 1. For instance, if a participant indicated 'I like it' for the presence of a feature and 'I dislike it' for its absence, this would place the feature

Table 1: Kano evaluation table

Response		Dysfunctional				
		I like it	I expect it	I am neutral	I can tolerate it	I dislike it
Functional	I like it	Q	A	A	A	O
	I expect it	R	I	I	I	M
	I am neutral	R	I	I	I	M
	I can tolerate it	R	I	I	I	M
	I dislike it	R	R	R	R	Q

Note: A = Attractive, O = One-dimensional, M = Must-be, I = Indifferent, R = Reverse, Q = Questionable

in the O category. A key part of the evaluation was identifying features within the Reverse (R) category, which indicates features that decrease satisfaction as they increase. Conversely, features in the Must-be (M) category, as highlighted by Matzler et al. [18], are fundamental and their absence can cause significant dissatisfaction. Our feature prioritization followed the hierarchy of M, O, A, and I.

Our analysis also includes evaluating the impact of each feature's presence or absence on customer satisfaction or dissatisfaction, using the Satisfaction Coefficient (SC) and Dissatisfaction Coefficient (DC), derived from the following Kano model formulae:

$$SC = \frac{A+O}{A+O+M+I} \tag{1}$$

$$DC = -\frac{M+O}{A+O+M+I} \tag{2}$$

These coefficients indicate the degree to which different features affect consumer satisfaction and dissatisfaction [4, 23]. A higher SC value suggests that enhancing a feature significantly increases perceived customer satisfaction, while a DC close to -1 implies a substantial increase in customer dissatisfaction when a feature is lacking or poorly implemented.

Finally, we used the self-stated importance scores from participants to rank these features, further providing a hierarchy of priorities. This step was particularly crucial because the Kano model, while effective in categorizing features, does not inherently consider the practicality of integrating multiple features concurrently, especially when faced with technical or financial limitations [16, 18].

3 RESULT

3.1 Kano classification and analysis

This study aimed to categorize healthcare robot features based on the Kano model using data from the two-dimensional questionnaire. We used the Kano evaluation table for this analysis, identifying the predominant Kano category for each feature based on the majority of responses. Detailed findings, including response counts, ratios, and dominant categories for each feature, are presented in Table 2.

3.1.1 Reverse features. A significant portion of participants (54.9%) labeled 'Animal-like appearance' in healthcare robots as a 'Reverse' feature, indicating it inversely affects their satisfaction. Essentially, equipping healthcare robots with animal-like appearances tends to decrease satisfaction among older adults.

3.1.2 One-dimensional features. 'One-dimensional' features identified were 'Medication Management' (32.8%) and 'Managing Illness and Monitoring Health' (31.6%). These features directly correlate with increased user satisfaction when provided or enhanced, and their absence or inadequacy can lead to dissatisfaction.

3.1.3 Attractive features. Eight features were categorized as 'Attractive': 'Frailty and Falling' (34.0%), 'Housework' (48.2%), 'Adaptability' (32.4%), 'Physical Decline Prevention and Therapy' (46.2%), 'Cognitive Decline Prevention and Therapy' (34.4%), 'Security and Safety Monitor' (43.1%), 'Meal Preparation' (49.8%), and 'Personality - Caring Personality' (31.2%). These features, while not expected by participants, significantly enhance satisfaction. Their absence, however, does not lead to dissatisfaction.

3.1.4 Indifferent features. Our analysis identified sixteen features as 'Indifferent' in the Kano model. These features, such as 'Bathing', have a neutral impact on customer satisfaction, with respondents showing neither satisfaction nor dissatisfaction with their presence or absence. This suggests these features, while present in healthcare robots, do not markedly affect overall user satisfaction.

3.1.5 Must-be features. None of the features were identified as 'Must-be' features for healthcare robots, indicating that participants did not consider any feature absolutely essential, thus not causing extreme dissatisfaction.

3.2 Satisfaction coefficient analysis

The data derived from the Kano questionnaire was instrumental in categorizing and prioritizing features for healthcare robot designs. However, this classification alone does not fully illustrate how strongly each feature impacts user satisfaction and dissatisfaction [4, 23]. To gain deeper insights, we calculated the SC and DC for each feature, based on formulas specified in equations 1 and 2. For instance, 'Medication Management' and 'Managing Illness and Monitoring Health', both identified as one-dimensional features, showed SCs of 0.67 and 0.65, respectively. These high SC values signify a substantial enhancement in customer satisfaction. They also had the highest DCs, suggesting that their absence or inadequate implementation could lead to considerable dissatisfaction among older adults. This finding supports their one-dimensional classification and underscores their vital role in design to avoid significant user dissatisfaction.

Moreover, the SC and DC values are crucial in the prioritization of features, particularly under design constraints that limit the feasibility of implementing all desired features. Comparing 'Housework' (SC: 0.81, DC: -0.39) with 'Physical Decline Prevention and Therapy' (SC: 0.72, DC: -0.29), both categorized as attractive features, reveals that 'Housework' has a more pronounced effect on satisfaction and is more critical in preventing dissatisfaction. In scenarios constrained by technical or financial resources, these coefficients offer vital guidance for strategically prioritizing features. Such insights are key in decision-making processes, especially when trade-offs between different features are necessary.

3.3 Perceived importance of features

Participants identified 'Frailty and Falling', 'Housework', 'Medication Management', 'Managing Illness and Monitoring Health', and 'Adaptability' as the most important features for healthcare robots. Conversely, 'Animal-like appearance', 'Large size', 'Male gender', and 'Bathing' were seen as less important. These findings are detailed in Table 2. While the Kano model offers valuable insights, it's not always sufficient for decision-making. For instance, 'Adaptability' and 'Caring personality' are both attractive features

Table 2: Analysis of responses and categorization of features

Feature	Kano model distribution N (%)						Category	Customer satisfaction coefficient		Importance	
	M	O	A	I	R	Q		Satisfaction	Disatisfaction	Rank	Mean (SD)
Medication Management	20 (7.9%)	83 (32.8%)	77 (30.4%)	59 (23.3%)	11 (4.3%)	3 (1.2%)	O	0.67	-0.43	3	3.74 (1.26)
Managing Illness and Monitoring Health	20 (7.9%)	80 (31.6%)	72 (28.5%)	63 (24.9%)	14 (5.5%)	4 (1.6%)	O	0.65	-0.43	4	3.65 (1.21)
Housework	18 (7.1%)	79 (31.2%)	122 (48.2%)	28 (11.1%)	2 (0.8%)	4 (1.6%)	A	0.81	-0.39	2	3.84 (1.10)
Physical Decline Prevention and Therapy	13 (5.1%)	56 (22.1%)	117 (46.2%)	55 (21.7%)	8 (3.2%)	4 (1.6%)	A	0.72	-0.29	6	3.60 (1.17)
Security and Safety Monitor	10 (4.0%)	62 (24.5%)	109 (43.1%)	60 (23.7%)	8 (3.2%)	4 (1.6%)	A	0.71	-0.30	8	3.52 (1.22)
Frailty and Falling	17 (6.7%)	85 (33.6%)	86 (34.0%)	58 (22.9%)	3 (1.2%)	4 (1.6%)	A	0.70	-0.41	1	3.89 (1.12)
Cognitive Decline Prevention and Therapy	10 (4.0%)	67 (26.5%)	87 (34.4%)	67 (26.5%)	20 (7.9%)	2 (0.8%)	A	0.67	-0.33	7	3.55 (1.27)
Meal Preparation	6 (2.4%)	30 (11.9%)	126 (49.8%)	71 (28.1%)	15 (5.9%)	5 (2.0%)	A	0.67	-0.15	13	2.96 (1.17)
Adaptability	35 (13.8%)	58 (22.9%)	82 (32.4%)	68 (26.9%)	8 (3.2%)	2 (0.8%)	A	0.58	-0.38	5	3.64 (1.10)
Personality - Caring personality	27 (10.7%)	54 (21.3%)	79 (31.2%)	75 (29.6%)	13 (5.1%)	5 (2.0%)	A	0.57	-0.34	17	2.68 (1.21)
Personality - Personality role match	22 (8.7%)	48 (19.0%)	80 (31.6%)	84 (33.2%)	14 (5.5%)	5 (2.0%)	I	0.55	-0.30	10	3.43 (1.31)
Personality - Human-robot personality match	10 (4.0%)	10 (4.0%)	76 (30.0%)	116 (45.8%)	34 (13.4%)	7 (2.8%)	I	0.41	-0.09	11	3.36 (1.13)
Personality - Socially communicative	21 (8.3%)	36 (14.2%)	59 (23.3%)	116 (45.8%)	18 (7.1%)	3 (1.2%)	I	0.41	-0.25	12	3.05 (1.26)
Mobility	15 (5.9%)	57 (22.5%)	74 (29.2%)	91 (36.0%)	11 (4.3%)	5 (2.0%)	I	0.55	-0.30	9	3.43 (1.22)
Social Communication/Isolation	4 (1.6%)	21 (8.3%)	76 (30.0%)	103 (40.7%)	44 (17.4%)	5 (2.0%)	I	0.48	-0.12	15	2.75 (1.20)
Facial Dimensions and Expressions	4 (1.6%)	9 (3.6%)	78 (30.8%)	105 (41.5%)	50 (19.8%)	7 (2.8%)	I	0.44	-0.07	19	2.54 (1.21)
Gender - Female	5 (2.0%)	18 (7.1%)	80 (31.6%)	121 (47.8%)	13 (5.1%)	16 (6.3%)	I	0.44	-0.10	14	2.80 (1.22)
Gender - Gender match	10 (4.0%)	11 (4.3%)	53 (20.9%)	150 (59.3%)	19 (7.5%)	10 (4.0%)	I	0.29	-0.09	20	2.45 (1.12)
Gender - Male	0 (0.0%)	3 (1.2%)	22 (8.7%)	173 (68.4%)	41 (16.2%)	14 (5.5%)	I	0.13	-0.02	25	2.06 (0.96)
Companionship	7 (2.8%)	24 (9.5%)	61 (24.1%)	112 (44.3%)	44 (17.4%)	5 (2.0%)	I	0.42	-0.15	16	2.73 (1.31)
Bathing	5 (2.0%)	10 (4.0%)	39 (15.4%)	103 (40.7%)	91 (36.0%)	5 (2.0%)	I	0.31	-0.10	24	2.20(1.19)
Size - Small	19 (7.5%)	15 (5.9%)	34 (13.4%)	169 (66.8%)	10 (4.0%)	6 (2.4%)	I	0.21	-0.14	18	2.65 (1.15)
Size - Size match	3 (1.2%)	4 (1.6%)	52 (20.6%)	163 (64.4%)	22 (8.7%)	9 (3.6%)	I	0.25	-0.03	21	2.45 (1.05)
Size - Large	0 (0.0%)	2 (0.8%)	8 (3.2%)	144 (56.9%)	91 (36.0%)	8 (3.2%)	I	0.06	-0.01	26	1.93 (0.95)
Appearance - Human-like appearance	3 (1.2%)	4 (1.6%)	70 (27.7%)	121 (47.8%)	48 (19.0%)	7 (2.8%)	I	0.37	-0.04	22	2.43 (1.09)
Appearance - Machine-like appearance	11 (4.3%)	8 (3.2%)	11 (4.3%)	176 (69.6%)	41 (16.2%)	6 (2.4%)	I	0.09	-0.09	23	2.38 (1.08)
Appearance - Animal-like appearance	1 (0.4%)	0 (0.0%)	24 (9.5%)	82 (32.4%)	139 (54.9%)	7 (2.8%)	R	0.22	-0.01	27	1.68 (0.95)

Note: A = Attractive, O = One-dimensional, M = Must-be, I = Indifferent, R = Reverse, Q = Questionable

with similar SCs and DCs. Yet, 'Adaptability' is rated higher in importance. In cases where a choice must be made, features with higher user importance, like 'Adaptability', should be prioritized. Integrating Kano model insights with user preferences, this strategy has the potential to enhance healthcare robot design.

4 DISCUSSION

This study uses the Kano model to categorize and prioritize 27 features of healthcare robots for older adults, providing key insights into user preferences and acceptance of this technology. First, the study reveals that not all features of healthcare robots are equally important for older adults' satisfaction and acceptance. 'Animal-like appearance', for example, emerged as a 'reverse' feature, aligning with previous research that suggests such designs are less favored in healthcare settings [6, 15, 31]. Features like 'Medical Management' and 'Managing Illness and Monitoring Health' were identified as one-dimensional features, enhancing satisfaction significantly.

Second, the study highlights a clear trend in the prioritization of functional features in healthcare robots. The majority of the features in the one-dimensional and attractive categories are related to functionality, underscoring a stronger link between user satisfaction and the robot's healthcare performance over its interaction traits. Functionality is closely related to usefulness, which significantly impacts the further acceptance and adoption of robots [3, 21]. This insight is crucial for developers, suggesting a greater focus on functional capabilities in future designs.

Third, the absence of 'must-be' features suggests that we are at the early stage of developing and deploying healthcare robots at home. This aligns with literature, which states that the healthcare robots at home are not widely available on the market [24]. Therefore, the current familiarity with healthcare robots among older adults might be limited, posing a challenge for older adults to pinpoint features they consider essential. As users become more acquainted with these technologies, it is likely that their expectations and capacity to identify indispensable features will develop.

The study has several limitations. First, the findings are confined to U.S. older adults and may not translate directly to other demographic groups or cultural contexts. Also, as healthcare robots are still emerging in U.S. homes, the study could not fully assess the impact of prolonged user experience with these technologies. Future research should consider longitudinal studies and explore diverse user groups to provide a more comprehensive understanding.

5 CONCLUSION

This study leverages the Kano model to delve into the preferences of older adults in the U.S. regarding healthcare robot features. A thorough survey encompassing 27 varied features led to the identification of critical features that elevate user satisfaction, with 'Medication Management' and 'Managing Illness and Monitoring Health' standing out, while features such as 'Animal-like appearance' were less favored. Our research distinctly shows a preference for functional features among users, crucial for fostering a user-centric approach to developing healthcare robots. Moreover, the study establishes a solid groundwork, enhancing our understanding of user preferences in this area and setting directions for future research in the development of healthcare robots.

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