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Research article

Data-Driven Design of an Automatic Shower for the Elderly: Integrating the Kano Model and K-Means Clustering

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Abstract: Automated devices designed for elderly users have become increasingly important in supporting independent living and addressing age-related challenges. Among these technologies, automatic shower devices play a key role in enhancing personal hygiene and reducing safety risks associated with conventional showering. This study applied the Kano model to identify factors influencing customer satisfaction with an automated shower device designed for older adults. Expert input was used to define and evaluate 25 quality elements across six dimensions, including washing, cleaning, safety, customer service, product-friendliness, and software–hardware integration. The results indicate that safety- and cleaning-related features—such as automatic disinfection, machine self-cleaning, automated emergency calls, emergency stop functions, and fall detection—exhibit high satisfaction coefficients, highlighting their importance in meeting elderly users' expectations. To further explore variation in user preferences, K-means clustering was used to segment respondents based on their Kano response patterns. Three distinct user clusters were identified, each demonstrating different feature prioritization strategies. One cluster emphasized comfort-enhancing features, such as body massage and automatic warm-air drying, while another placed greater importance on essential safety functions, including fall detection and emergency alerts. By integrating the Kano model with K-Means clustering, this study proposes a data-driven, customer-centric design framework that supports informed decision-making in assistive technology development. The findings enable designers and manufacturers to balance core safety requirements with differentiated features tailored to diverse elderly user segments, ultimately enhancing usability, independence, and overall user satisfaction.

Keywords: Kano model; K-mean clustering; customer satisfaction; data-driven design; automated devices

1. Introduction

Recently, automated devices designed explicitly for older adults have gained significant importance [1, 2]. As technological advancements continue to transform various aspects of our lives, healthcare and assistance for older adults are no exception. The development of automated devices catering to the specific needs of the elderly population holds immense potential to improve their overall quality of life and independence [2, 3]. The aging population faces unique challenges related to mobility, health, and daily tasks that are often physically demanding [4-6]. Automated devices offer innovative solutions to these challenges by incorporating advanced technologies and intelligent features [7]. Such devices are designed to assist older adults with daily activities, promoting safety, convenience, and a sense of empowerment [8, 9]. The importance of automated devices for older adults goes beyond mere convenience. They contribute significantly to the physical and emotional well-being of seniors, allowing them to maintain independence and dignity [10]. By reducing physical strain and potential hazards, these devices promote a sense of confidence and self-sufficiency, leading to improved mental health and overall satisfaction [11, 12]. Furthermore, automated devices can provide peace of mind for caregivers and family members who may have concerns about the safety and well-being of their elderly loved ones. With the assistance provided by these devices, caregivers can be reassured that their elderly relatives receive the necessary support and care they need while minimizing the risk of accidents and injuries [13, 14].

Automated devices address mobility and health challenges among older adults by providing creative solutions to support daily tasks and increase independence. These devices enable a higher quality of life for the elderly by streamlining and simplifying tasks such as medication management [15, 16], home monitoring [17-19], and personal assistance [20, 21]. One area where the development of automated devices has shown great promise is personal hygiene [22, 23], particularly in automatic shower devices. Traditional showering can be physically strenuous and pose risks for elderly individuals, such as slips and falls [24]. Elderly individuals often face challenges with bathing, including difficulty getting in and out of the bathtub and the need for assistance due to safety concerns, highlighting the importance of innovative solutions that can provide greater independence and support [25]. A mechanical shower device can alleviate these concerns by incorporating automatic soaping, temperature control, and safety mechanisms [25, 26]. Despite the growing importance of automated devices designed for older people and their potential to enhance their quality of life and independence, a greater understanding is needed concerning the specific customer satisfaction factors that should be prioritized in designing such devices [27, 28]. While existing studies have explored the benefits of automated devices for older adults, few have applied a systematic approach [25, 26]. Therefore, more research is needed to fill the knowledge gap and to comprehensively understand the unique needs and preferences of older adults regarding automated devices, particularly for personal hygiene.

This study aims to bridge this gap by applying the Kano model to identify and evaluate the coefficients of customer satisfaction and dissatisfaction for key features of an automated shower device for older adults. K-Means clustering is further applied to segment users by their Kano response patterns, revealing distinct groups with shared preferences and expectations. While the combined use of the Kano model and clustering techniques has been explored in previous studies, the novelty of this research lies in its application to an elderly-centered automated shower system, supported by expert-driven feature elicitation and cluster-level interpretation explicitly linked to design implications for assistive technologies. This integrated approach enables a data-driven understanding of heterogeneous user needs across elderly subpopulations and supports more targeted, user-centered design strategies. The findings provide practical guidance for developing automated shower devices that enhance safety, usability, and overall well-being among elderly users.

2. Literature review

2.1 Application of the Kano Model in Data-Driven Design

The Kano model is widely recognized as an effective method for identifying and prioritizing customer needs by assessing their impact on overall satisfaction. The Kano model enables developers to discern essential, expected, and potentially agreeable elements by categorizing features into basic, performance, and agreeable categories [29-31]. A BERT-TCBAD-Kano-based method was developed to extract and prioritize user requirements from online reviews [32]. By combining sentiment analysis, complaint classification, and Kano evaluation, the study achieved a 30% improvement in prediction accuracy over the traditional Kano model, supporting more effective user-centered product design. Wang et al. [33] integrate the Kano model into a UGC-driven framework to identify how different product attributes influence user satisfaction and dissatisfaction. By analyzing user-generated content and clustering user needs, the Kano model categorizes factors that affect continuance and discontinuance intentions, offering a data-driven approach to understanding the user experience. Cavacece et al. [34] apply the Kano model to explore the nonlinear relationship between digital health service quality and user satisfaction, highlighting that distinct service attributes affect satisfaction and dissatisfaction differently. It advances prior research by moving beyond linear assumptions and emphasizing user-centered design in digital health contexts. Li et al. [35] apply the Kano model, along with satisfaction and sensitivity coefficients, to evaluate functional requirements for health-focused e-sports chairs. By identifying essential, one-dimensional, and attractive features, the research offers a hierarchical design strategy that enhances user satisfaction while optimizing production through non-differentiated functions. These studies reinforce the methodological grounding of our research and highlight the growing trend of using Kano-based frameworks to guide the design of personalized, health-supportive technologies.

2.2 K-Means clustering

K-Means clustering is widely used for customer segmentation due to its simplicity and efficiency. This algorithm operates by grouping customers into distinct clusters based on similarities in their behaviors, preferences, or usage patterns, making it a powerful tool for uncovering hidden structures in large datasets [36]. Its core strengths lie in its computational speed and ease of implementation, enabling it to handle high-dimensional data efficiently. K-Means is particularly effective in applications such as market segmentation [37], personalized marketing, and behavioral profiling, where identifying homogeneous groups within diverse customer bases can lead to more targeted strategies and optimized service offerings. Despite its simplicity, it often yields meaningful insights that can drive decision-making in both business and engineering contexts. To enhance the traditional approach by introducing a nearest-neighbor density matrix and adaptive cluster selection [38], overcoming limitations such as sensitivity to initial centers and predefined cluster numbers. The improved method offers higher accuracy and stability, making it well-suited for analyzing customer behavior and demand patterns in power systems. Zhao et al. [39] enhance customer segmentation by extending the traditional K-Means clustering method with an elastic net penalty term, addressing challenges in high-dimensional data arising from weekly RFM variables. The improved method offers better clustering accuracy and variable selection, making it more effective for analyzing online customer behavior in omnichannel retail settings. Fang and Liu [40] applies and improves the K-Means algorithm for customer segmentation, aiming to enhance CRM effectiveness. It introduces a customer value evaluation system using AHP and clustering to classify customers. To address limitations of traditional K-Means, the study proposes two improved algorithms—one that automatically determines the optimal number of clusters, and another that boosts efficiency by combining sampling and agglomeration. The approach supports more accurate customer value analysis and decision-making in enterprise environments.

The review of prior research supports the suitability of both the Kano model and K-Means clustering as methodological foundations for this study. The Kano model has been widely used to classify user requirements into Must-Be, One-Dimensional, Attractive, Indifferent, and Reverse categories, enabling systematic feature prioritization based on their impact on user satisfaction. Its application across diverse domains demonstrates its effectiveness in capturing nonlinear relationships between product attributes and user perceptions. In the context of automated shower design for older adults, the Kano model provides a user-centered framework for distinguishing essential safety-related features from value-adding functions. The integration of K-Means clustering further enhances this approach by identifying latent user segments with differing expectations. Prior studies have shown that clustering techniques are effective for preference-based segmentation, supporting more targeted and inclusive design strategies. When combined with the Kano framework, clustering reveals how different user groups prioritize feature categories, offering deeper insight for design decision-making. Overall, the combined use of the Kano model and K-Means clustering aligns with best practices in user-centered product development and strengthens the analytical depth of this study. Together, these methods support a design approach that is both functionally responsive and adaptive to demographic diversity, making them well-suited to the research objectives.

3. Methods

3.1 Kano model

The Kano model considers both the subjective aspects of satisfaction and dissatisfaction as well as the objective elements of functionality [41-43]. It seeks to understand how a product or service's features and attributes influence user acceptance and satisfaction. The Kano model is critical and can be divided into five categories, as shown in Figure 1. These classifications are based on the varying levels of acceptance and satisfaction they provide users [44-46].

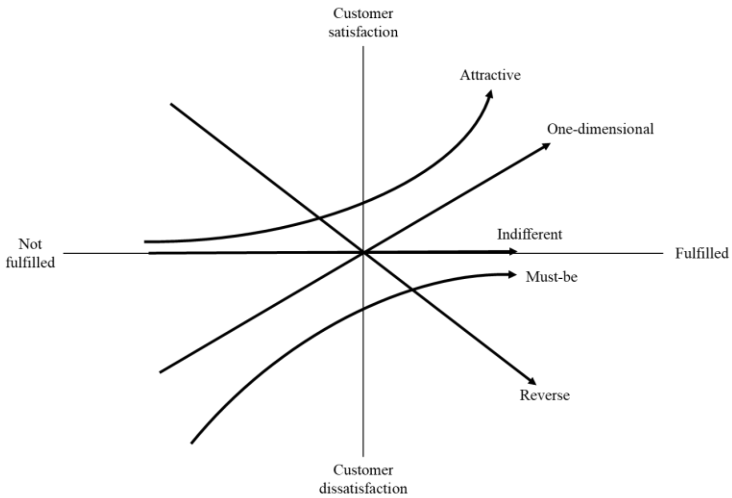

Figure 1. The Kano model [28]

Based on their characteristics, the Kano model systematically classifies user requirements and ranks them by the importance of achieving user satisfaction [47, 48]. This model offers a helpful framework for recognizing and satisfying users' needs and expectations. The Kano model can be used by businesses to categorize user requirements by their impact on customer satisfaction. The Kano model helps prioritize resource allocation and effort in product development by categorizing user requirements [49]. It enables companies to identify and focus on the key factors that significantly impact user satisfaction. This strategy allows businesses to allocate resources wisely and deliver goods and services that meet or exceed customer expectations [50]. The Kano model also offers a deeper comprehension of the dynamic nature of user requirements. It acknowledges that user satisfaction is influenced by various factors, including users' perceptions and expectations, as well as the presence or absence of attributes. Overall, the Kano model provides a comprehensive framework for categorizing and prioritizing user requirements based on their impact on user satisfaction. Businesses can use this model to make informed decisions about resource allocation and product development strategies, ultimately improving user satisfaction and gaining a competitive advantage in the market [51, 52].

3.2 Participants

A comprehensive participant study was conducted, specifically targeting adults aged 60 or older. This study was conducted as a non-invasive, questionnaire-based investigation of design requirements and user preferences for an automatic shower system for elderly users, using the Kano model. A total of 63 elderly participants were recruited using convenience sampling from local community centers and public residential areas. Inclusion criteria required participants to be aged 60 years or older, in generally good physical condition, and capable of independently understanding and completing the questionnaire. The study did not involve medical treatment, physical experimentation, or prototype testing, nor did it collect sensitive personal or health-related information. Participation was voluntary, and all participants were clearly informed of the study objectives and procedures before participation. Informed consent was obtained before data collection. Participant anonymity and data confidentiality were strictly maintained throughout the study. This cross-sectional study aimed to evaluate their unique requirements and preferences in depth. Subsequently, the collected data were analyzed using the widely recognized Kano model, a methodology commonly used for evaluating customer satisfaction. To further explore patterns in user expectations, K-Means clustering was applied to segment participants into distinct groups based on their Kano response profiles. This combined approach enabled a deeper understanding of the heterogeneity among elderly users, offering actionable insights for the development of more personalized and effective automated shower device designs.

3.3 Developing quality evaluation dimensions and characteristics

The initial set of product features was identified through a structured expert brainstorming process involving a multidisciplinary panel with expertise in product design, mechanical engineering, and elderly care-related system design. The expert panel consisted of five professionals selected using purposive sampling based on their domain expertise and practical experience relevant to assistive shower system design. The panel included specialists in human factors engineering, automation engineering, and elderly care nursing, ensuring coverage of ergonomic design, system functionality, and user safety considerations. Experts were selected based on the following criteria: (1) a minimum of five years of professional or research experience in their respective fields, (2) direct involvement in product design, automation systems, or elderly care services, and (3) familiarity with assistive technologies or safety-oriented system design. The panel size was considered appropriate for early-stage feature identification and was consistent with exploratory engineering design practices. The process was conducted iteratively. In the first round, experts independently proposed potential features based on prior experience, relevant literature, and practical design considerations. These features were then reviewed collectively, and redundant or technically infeasible items were merged or removed through group discussion. Consensus was achieved through iterative deliberation, focusing on features that were relevant, easy to understand for elderly users, and suitable for Kano-based evaluation. The process continued until no new features emerged, yielding a final set of 25 product features for the Kano survey. A total of 25 quality evaluation elements across six dimensions were identified. The six dimensions of functional requirements include washing, cleaning, safety, customer service and support, product-friendliness, and software-hardware integration. The 25 quality evaluation elements and six dimensions are shown in Table 1.

Table 1. Quality evaluation elements and dimensions of customer requirements

Dimensions	Elements		Description
Washing Function	A1	Automatic soaping	Automatic dispensing and application of soap to reduce manual effort
	A2	Automatic water temperature control	Automatic regulation of water temperature for comfort and safety
	A3	Automatic warm air drying	Integrated warm air system for body drying after showering
	A4	Manual control	User-operated controls allowing manual adjustment of shower functions
	A5	Surround water jets	Multi-directional water jets provide full-body water coverage
	A6	Shower heads	Adjustable or multiple shower heads for improved washing efficiency
	A7	Body massage	Water pressure–based massage function to enhance comfort and relaxation
	A8	Ozone therapy	Use of ozone-treated water for hygiene and odor reduction
	A9	Color therapy lights	An integrated lighting system intended to enhance relaxation or mood
Cleaning Function	B1	Automatic Disinfection	Automated disinfection process to maintain hygiene after use
	B2	Automatic Machine self-cleaning	Self-cleaning mechanism to reduce maintenance requirements

Table 2. Quality evaluation elements and dimensions of customer requirements (continue)

Dimensions	Elements		Description
Safety Function	C1	Automated emergency call	Automatic alert system activated during emergencies
	C2	Automated emergency stop	An immediate system shutdown function to prevent accidents
	C3	Fall Detection	Sensor-based system to detect user falls and trigger safety responses
Customer Service and Support	D1	Safety assurance	Measures ensuring compliance with safety standards and user protection
	D2	Product guarantee	Warranty and assurance covering product performance and reliability
	D3	On-site service	Availability of maintenance and repair services at the user's location
Product-friendliness	E1	Easy to set up	Simple installation process requiring minimal effort or tools
	E2	Lightweight	Design emphasizing reduced weight for easier handling and installation
	E3	Duration	Expected service life and durability of the product
	E4	Comfortable seat	Ergonomically designed seating to support comfort and stability
Software-Hardware Integration	F1	Mobile application control	Smartphone-based control interface for system operation
	F2	Music Player	Integrated audio system for entertainment during use
	F3	Voice command	Voice-activated control for hands-free operation
	F4	Memory setup	System capability to store and recall personalized user settings

Table 3. Demand attribute definitions

Demand attribute	Definitions
Must-be (M)	Customers tend to be more dissatisfied with less functional products. However, even if the product becomes highly active, customer satisfaction remains at a neutral level.
One-dimensional (O)	Increased functionality typically results in greater customer satisfaction.
Attractive (A)	Customers generally experience higher satisfaction with more functional products, but achieving greater functionality requires more effort.
Indifferent (I)	Customers tend to exhibit a neutral level of satisfaction regardless of whether the product is fully functional or dysfunctional.
Reverse (R)	Customers are likely to experience a decrease in satisfaction if a product's functionality is reduced, and the level of satisfaction is typically inversely proportional to the extent of the reduction.

The Kano questionnaire is a structured survey tool used to assess customer needs and the importance of product or service quality to users. The two-way Kano questionnaire is an effective tool for comprehensively understanding consumer demands and preferences, including individual quality elements (demand attributes) and overall satisfaction. Table 3 illustrates the Kano two-way questionnaire format. The questionnaire utilized a Kano two-dimensional model of quality, which organizes customer preferences into five distinct categories. These categories were thoroughly examined to understand their implications. Each quality element being investigated is associated with positive and negative questions. Participants are provided with five options to select from for each question. The questionnaire was designed to capture the product's basic requirements, desired features, and any surprises or delights that could exceed customer expectations, taking a comprehensive approach. This allowed for a more thorough evaluation of customer satisfaction and helped identify key areas for product improvement. The Kano quality attribute determination matrix was utilized to classify the quality level of each demand attribute. To ensure content validity and clarity, the questionnaire items were adapted from established Kano model studies and reviewed for relevance to the context of automatic shower system design for elderly users. All questions were presented in clear, simple language appropriate for elderly respondents. Before the main data collection, the questionnaire was reviewed for clarity and completeness to minimize ambiguity and misunderstanding, as presented in Table 4.

Table 4. The Kano two-way questionnaire format

Customer Requirement	Question	Answer
Automatic water temperature control	What would you think of an automatic shower device for the elderly that controls water temperature?	□ Satisfying □ Should be so □ Does not matter □ Tolerable □ Disagreeable
	What would you think of an automatic shower device for the elderly that has no automatic water temperature control?	□ Satisfying □ Should be so □ Does not matter □ Tolerable □ Disagreeable

Table 5. Kano evaluation matrix

	Available / Unavailable	Satisfying	Should be so	Negative Does not matter	Tolerable	Disagreeable
Positive	Satisfying	Q	A	A	A	O
	Should be so	R	I	I	I	M
	Does not matter	R	I	I	I	M
	Tolerable	R	I	I	I	M
	Disagreeable	R	R	R	R	Q

3.5 Importance coefficients

Importance coefficients, such as customer satisfaction and dissatisfaction values, are employed to compare the significance of different demands classified under the same attribute. These coefficients help determine which features are essential for raising customer satisfaction and allow a more accurate assessment of customer preferences. The customer satisfaction coefficient is used to assess the impact of customer satisfaction and dissatisfaction, and can be calculated as

$$\text{Satisfaction Coefficient (SC)} = \frac{(A+O)}{(A+O+M+I)} \tag{1}$$

$$\text{Dissatisfaction Coefficient (DC)} = \frac{(O+M)}{(A+O+M+I)} \tag{2}$$

The satisfaction and dissatisfaction values range from 0 to 1. A higher satisfaction value, closer to 1, indicates that providing the attribute can enhance satisfaction. On the other hand, a higher dissatisfaction value, closer to 1, indicates that not providing the attribute can lead to greater dissatisfaction [55]. Note that the dissatisfaction coefficient (DC) is reported as a negative value to indicate the direction of dissatisfaction, consistent with conventional Kano model interpretations. In this study, the negative sign is retained to explicitly indicate the potential decrease in customer satisfaction when a feature is absent. For interpretation purposes, a larger absolute DC value indicates a stronger effect of dissatisfaction.

3.6 K-Means clustering

K-Means clustering is one of the most widely used unsupervised machine learning algorithms for data partitioning. The algorithm aims to divide a set of *n* data points into *k* distinct, non-overlapping clusters, where each data point belongs to the cluster with the nearest mean (centroid). This method is particularly suitable for customer segmentation, behavioral analysis, and feature preference grouping, especially when the objective is to explore underlying patterns in large-scale data without prior labels. K-Means minimizes the within-cluster sum of squares (WCSS) [56], also known as inertia, which represents the variance within each cluster. The objective is to locate:

$$arg\min \sum_{i=1}^{k} \sum_{x \in S_i} \|x - \mu_i\|^2 \quad (3)$$

Where:
$k = number\ of\ clustering.$
$S_i =\ set\ of\ data\ point\ assigned\ to\ cluster\ i$
$\mu_i =\ mean\ (centroid)\ of\ cluster\ i$
$\|x - \mu_i\|^2 =\ squared\ Euclidean\ distance\ between\ data\ point\ x\ and$
$its\ cluster\ centroid.$
Algorithmic Steps:

Initialization: Select k initial centroids, either randomly or using an improved method such as K-Means++ to improve convergence. Assignment Step: Assign each data point x_j to the cluster whose centroid μ_i is closest, based on the Euclidean distance:

$$Cluster(x_j) arg_i \min \|x - \mu_i\| \quad (4)$$

Update Step: Recalculate each cluster's centroid by taking the mean of all points assigned to that cluster:

$$\mu_i = \frac{1}{|S_i|} \sum_{x \in S_i} x \quad (5)$$

Iteration and Convergence: Repeat the assignment and update steps until the centroids no longer change significantly or a predefined maximum number of iterations is reached. Choosing the Optimal Number of Clusters (k). One of the key challenges in K-Means clustering is determining the most appropriate number of clusters. Common techniques include: the Elbow Method: plotting the WCSS for different values of k and identifying the "elbow" point where the rate of decrease changes sharply. Silhouette Score: Measuring how similar an object is to its own cluster compared to other clusters. Domain Knowledge: Leveraging prior understanding of the user base or problem context to select a meaningful *k*. In this research, K-Means clustering was applied to numerically encoded Kano response data (e.g., A = 1, O = 2, M = 3, I = 4, R = 5) to segment elderly participants based on their preference patterns across 25 features of an automatic shower device. The optimal number of clusters was determined using a combination of the elbow method and interpretability of the output. This enabled the identification of distinct user groups, each with specific preferences for Must-Be, Attractive, or One-Dimensional features. By incorporating K-Means clustering alongside the Kano model, this study offers a robust approach to user segmentation, enabling designers to prioritize feature sets according to specific needs and latent patterns within different elderly subgroups.

4. Results and Discussion

4.1 Classification and analysis of Kano demand attributes

A total of 63 valid questionnaires were collected, with participants comprising 54% men and 46% women. The participants were aged 60 or older, with a mean age of 70.85 years (SD = 3.29). For the Kano two-dimensional quality analysis, respondents were instructed to indicate their perceived satisfaction with six dimensions comprising 25 quality elements. For each quality element, the Kano category was determined by the response category with the highest percentage: Attractive (A), One-Dimensional (O), Must-Be (M), Indifferent (I), or Reverse (R). This dominant category was assigned as the representative Kano classification, reflecting the predominant user perception of each feature in accordance with standard Kano model practices. A total of 25 quality elements were evaluated, as given in Table 5. Out of these, seven were identified as "Attractive" to customers, meaning they positively impacted customer satisfaction and loyalty. Another seven elements were classified as "One-Dimensional," meaning they were considered essential by customers but did not necessarily increase customer loyalty or satisfaction. Four elements were identified as "Must-Be," meaning they were crucial to meeting customer expectations, and their absence would lead to dissatisfaction. Seven other elements were classified as "Indifferent," meaning customers did not consider them positive or negative in terms of their impact on satisfaction and loyalty. Finally, none of the 25 quality elements were classified as "Reverse," indicating that none negatively impacted customer satisfaction or loyalty.

Table 6. Kano quality element percentage and classification

Dimensions		Elements	A (%)	O (%)	M (%)	I	R (%)	Kano
Washing Function	A1	Automatic soaping	48	24	22	6	0	A
	A2	Automatic water	22	13	43	22	0	M
	A3	Automatic warm air drying	22	38	25	14	0	O
	A4	Manual control	21	43	21	16	0	O
	A5	Surround water jets	17	48	19	16	0	O
	A6	Shower heads	43	8	19	30	0	A
	A7	Body massage	54	5	3	38	0	A
	A8	Ozone therapy	37	2	2	60	0	I
	A9	Color therapy lights	30	2	2	67	0	I
Cleaning Function	B1	Automatic Disinfection	59	19	6	16	0	A
	B2	Automatic Machine self-	54	16	10	21	0	A
Safety Function	C1	Automated emergency call	21	48	22	10	0	O
	C2	Automated emergency stop	17	51	19	13	0	O
	C3	Fall Detection	44	29	19	8	0	A
Customer Service and Support	D1	Safety assurance	13	60	22	5	0	O
	D2	Product guarantee	22	13	43	22	0	M
	D3	On-site service	25	44	22	8	0	O
Product-friendliness	E1	Easy to set up	32	19	29	21	0	A
	E2	Lightweight	27	2	16	56	0	I
	E3	Duration	21	30	37	13	0	M
	E4	Comfortable seat	21	19	41	19	0	M
Software–Hardware Integration	F1	Mobile application control	19	2	10	60	10	I
	F2	Music Player	38	5	10	48	0	I
	F3	Voice command	25	5	3	63	3	I
	F4	Memory setup	27	8	10	56	0	I

4.1.1 Attractiveness

Seven quality elements were identified as attractive to customers, which positively affected their satisfaction and loyalty. Elements such as "Automatic Soaping" and "Shower Heads" can enhance the shower experience by providing convenience and comfort. "Body Massage" is an added feature that helps customers relax and reduce stress while showering [57]. "Automatic Machine Self-Cleaning" and "Automatic Disinfection" help customers maintain hygiene and cleanliness without manual cleaning. A "Fall Detection" safety feature can help prevent accidents and ensure customers' well-being. Lastly, "Ease of Setup" can help customers quickly and easily install and use the product, increasing their satisfaction.

4.1.2 One-dimensional

"Automatic Warm Air Drying," "Manual Control," "Surround Water Jets," "Automated Emergency Call," "Automated Emergency Stop," "Safety Assurance," and "On-Site Service" were all classified as one-dimensional; increasing functionality can typically result in greater customer satisfaction. While these one-dimensional quality elements are essential for meeting customer expectations, companies should continue offering these critical features. They should enhance these elements by adding functionality, which can lead to greater customer satisfaction and loyalty. For example, "Automatic Warm Air Drying" is an essential feature for drying off after a shower, but a more advanced feature could be an adjustable temperature setting, which would enable the customer to customize the drying temperature. Similarly, "Surround Water Jets" can be enhanced by adding different pressure settings or patterns, offering customers a more customized shower experience. "Automated Emergency Call" and "Automated Emergency Stop" are essential safety features customers expect to include in the product. However, offering additional safety features can help differentiate a product from its competitors. "Safety Assurance" can be enhanced by providing certifications or warranties that assure customers that the product is safe and reliable. "On-Site Service" can be improved by offering additional services, such as installation or maintenance, to enhance the customer experience further.

4.1.3 Must-be

The quality elements "Automatic Water Temperature Control," "Product Guarantee," "Duration," and "Comfortable Seat" were all classified as must-be, indicating that their absence can lead to customer dissatisfaction. The must-be quality elements are customers' basic requirements for the product. Customers will likely be dissatisfied with the product if any of these elements need to be added or are not up to standard. For example, "Automatic Water Temperature Control" is a must-have feature, ensuring customers can shower comfortably and safely without manually adjusting the temperature. "Product Guarantee" is another must-have element, as customers expect a certain level of quality and reliability from the product. A guarantee can provide them with confidence and peace of mind. "Duration" is also a must-have element, as customers expect the product to last for a reasonable amount of time without requiring frequent repairs or replacement. A product that fails to meet this requirement is likely to result in customer dissatisfaction. Similarly, a "Comfortable Seat" is a must-have feature, especially for customers with disabilities or elderly customers who may require additional support and comfort. While these must-be quality elements are essential for meeting customer expectations and preventing dissatisfaction, they do not necessarily increase customer satisfaction or loyalty. Companies should also focus on enhancing the quality of their products to differentiate themselves from competitors and improve customer satisfaction and loyalty.

4.1.4 Indifferent

The quality elements of "Ozone Therapy," "Color Therapy Lights," "Lightweight," "Mobile Application Control," "Music Player," "Voice Command," and "Memory Setup" were all classified as indifferent, indicating that their presence or absence would not likely affect customer satisfaction in any significant way. Indifferent quality elements do not significantly impact customer satisfaction, and their presence or absence does not significantly affect a customer's purchase decision. For example, "Ozone Therapy" and "Color Therapy Lights" can provide additional health benefits and relaxation, but they are not essential for a satisfactory shower experience. Similarly, "Lightweight" is a desirable feature, but it is unlikely to significantly affect customer satisfaction because it has no direct effect on the product's functionality. "Mobile Application Control," "Music Player," "Voice Command," and "Memory Setup" are additional features that can enhance the overall shower experience. However, their absence is likely to still result in customer satisfaction. These features may appeal to some customers, but they are optional for meeting the basic requirements of a shower.

4.1.5 Reverse

The Reverse classifications for mobile application control and voice command indicate that these features were perceived as undesirable by some elderly users. Mobile application control may increase usability complexity and cognitive load, requiring familiarity with smartphones and application management, thereby reducing perceived ease of use. Similarly, voice command functions may be viewed as unreliable or uncomfortable in bathroom environments due to speech recognition issues, background noise, or privacy concerns. These findings suggest that advanced digital interaction features may conflict with elderly users' preferences for simplicity and predictability and should therefore be treated as optional rather than core design elements in assistive technologies.

4.2 Results of customer satisfaction and dissatisfaction coefficients

The Kano model is a framework for understanding customer satisfaction and prioritizing features based on how customers perceive them. The dimensions and elements listed in the result are the various features that could be included in an automatic shower device for the elderly. The satisfaction and dissatisfaction coefficients indicate the perceived importance of each feature and the level of satisfaction or dissatisfaction it would evoke in a customer. In Figure 2, the X-axis center line represents the average extent of satisfaction for the 25 quality elements, while the Y-axis center line represents moderate dissatisfaction. The satisfaction and dissatisfaction coefficients indicate the magnitude of these factors, with values ranging from 0 to 1. When the quality element improves, a customer satisfaction coefficient close to 1 indicates a significant increase in perceived satisfaction. If the quality element remains unsatisfactory, an extent of dissatisfaction coefficient closer to -1 indicates a significant increase in perceived dissatisfaction [53]. Based on the coefficients listed in Table 6, clear product development priorities can be identified. Safety and cleaning functions should be treated as first-level priorities, as they exhibit high satisfaction coefficients and strong dissatisfaction effects when absent. In particular, automatic disinfection and Machine self-cleaning (B1 and B2), together with automated emergency call, emergency stop, and fall detection (C1–C3), represent core system requirements that directly influence user trust and acceptance. The second level of prioritization includes washing-related features with high satisfaction coefficients, such as automatic soaping (A1), surround water jets (A5), shower heads (A6), and body massage (A7), which primarily enhance comfort and perceived value. In contrast, features such as automatic water temperature control (A2) and color therapy lights (A9) show limited impact on satisfaction. Customer service and support features, particularly safety assurance (D1) and on-site service (D3), also contribute strongly to satisfaction and should be integrated into the overall product–service strategy. Product-friendliness attributes, including easy setup (E1) and product duration (E3), support usability and lifecycle performance and can be treated as secondary priorities. By comparison, software–hardware integration features (F1–F4) exhibit relatively low satisfaction coefficients and should be considered optional enhancements rather than core design requirements. Overall, the satisfaction coefficient analysis supports a structured prioritization strategy that emphasizes safety and hygiene first, followed by comfort-related features, while deprioritizing low-impact digital functions.

4.3 Cluster Analysis of User Requirements Using K-Means

To explore distinct patterns in user preferences for an Automatic Shower Device for the Elderly, K-Means clustering was employed. This unsupervised learning method was selected due to its effectiveness in partitioning users based on multidimensional categorical response data—in this case, the Kano responses (Attractive, One-dimensional, Must-be, Indifferent, and Reverse) to 25 product features. Based on the elbow method and interpretability considerations, the analysis was conducted with three clusters (k=3). The optimal number of clusters was determined using the elbow method by examining the relationship between the number of clusters (k) and the within-cluster sum of squares (WCSS). As shown in the elbow plot in Figure 3, WCSS decreased substantially from 10,483.28 at k = 1 to 2,660.81 at k = 3, after which the rate of reduction became less pronounced (e.g., 1,396.01 at k = 4 and 996.80 at k = 5). This noticeable change in the rate of WCSS reduction indicates an elbow at k = 3. Beyond this point, increasing the number of clusters yields only marginal improvements at the expense of interpretability. Therefore, k = 3 was selected as an appropriate balance between clustering performance and practical interpretability. To further assess cluster quality and robustness, internal validation was conducted using silhouette analysis. For the selected solution with k = 3, the average silhouette score was 0.47, indicating acceptable cluster separation and supporting the suitability of the clustering structure for exploratory, design-oriented analysis. The analysis revealed three distinct user clusters, as shown in Table 7, each representing a unique pattern of prioritization of product requirements. The validity of the clustering results was reinforced through multiple observations. First, a clear separation in response patterns was evident when the data were projected into a two-dimensional space using Principal Component Analysis (PCA)[56], indicating that the clusters captured meaningful variance among respondents. The distribution of Kano response types—Attractive (A), One-dimensional (O), Must-be (M), Indifferent (I), and Reverse (R)—was analyzed across the three identified clusters to gain a deeper understanding of each user group's underlying preferences. The results are summarized in Table 7. Each cluster exhibits a distinct prioritization pattern, reflecting the diversity of user expectations regarding the product features.

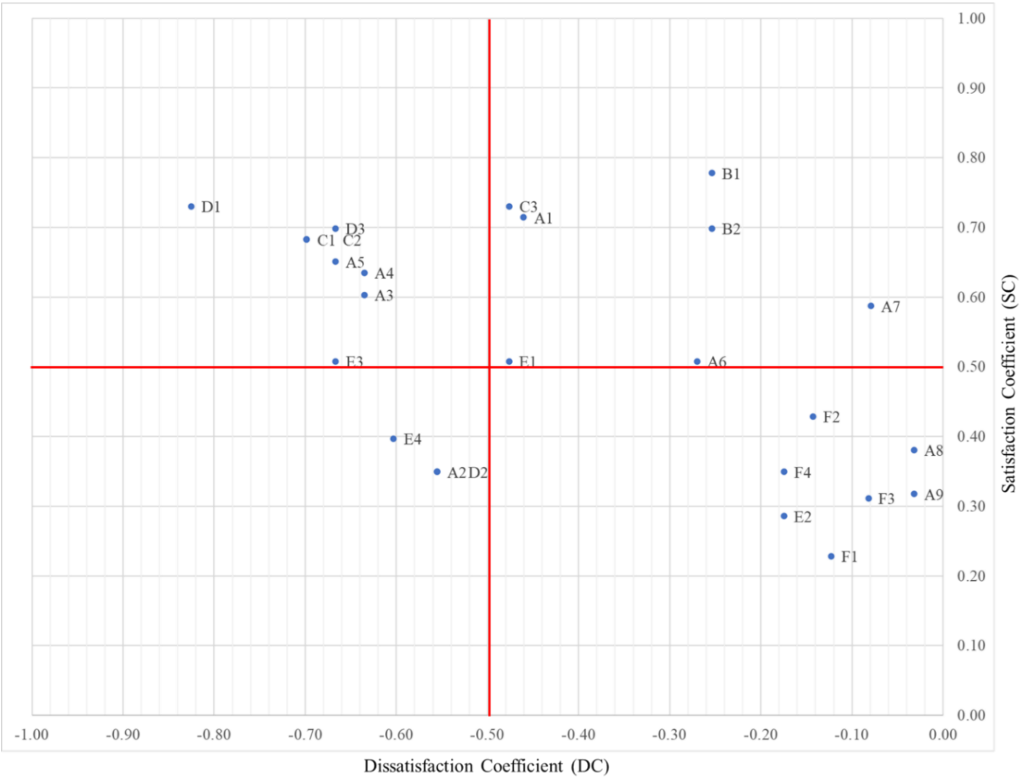

Figure 2. Customer satisfaction matrix

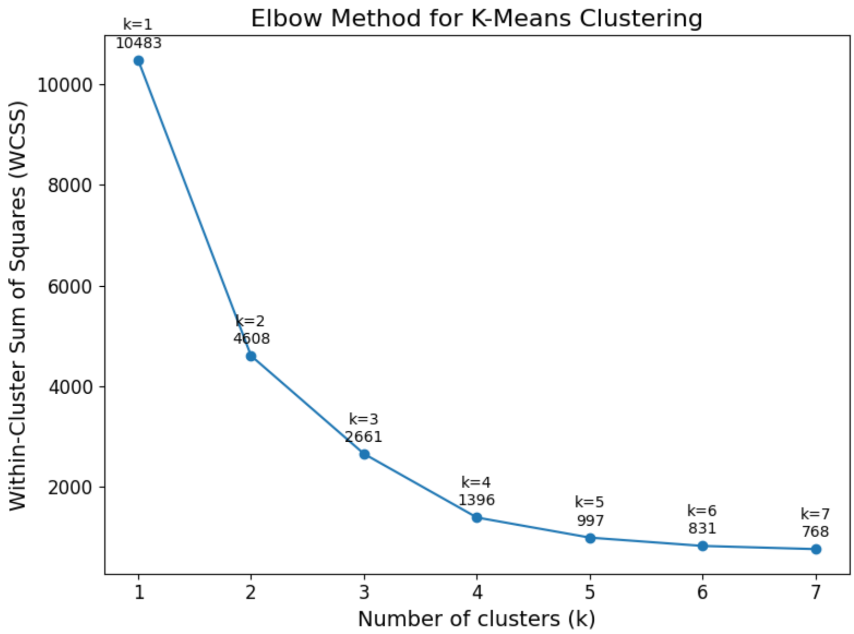

Figure 3. The elbow method is used to determine the optimal number of clusters for K-Means analysis.

Table 7. Customer satisfaction coefficients

Dimensions		Elements	Kano Classification	SC	DC
Washing Function	A1	Automatic soaping	A	0.71	-0.46
	A2	Automatic water temperature control	M	0.35	-0.56
	A3	Automatic warm air drying	O	0.60	-0.63
	A4	Manual control	O	0.63	-0.63
	A5	Surround water jets	O	0.65	-0.67
	A6	Shower heads	A	0.51	-0.27
	A7	Body massage	A	0.59	-0.08
	A8	Ozone therapy	I	0.38	-0.03
	A9	Color therapy lights	I	0.32	-0.03
Cleaning Function	B1	Automatic Disinfection	A	0.78	-0.25
	B2	Automatic Machine self-cleaning	A	0.70	-0.25
Safety Function	C1	Automated emergency call	O	0.68	-0.70
	C2	Automated emergency stop	O	0.68	-0.70
	C3	Fall Detection	A	0.73	-0.48
Customer Service and Support	D1	Safety assurance	O	0.73	-0.83
	D2	Product Guarantee	M	0.35	-0.56
	D3	On-site service	O	0.70	-0.67
Product-friendliness	E1	Easy to set up	A	0.51	-0.48
	E2	Lightweight	I	0.29	-0.17
	E3	Duration	M	0.51	-0.67
	E4	Comfortable seat	M	0.40	-0.60
Software-Hardware Integration	F1	Mobile application control	I	0.23	-0.12
	F2	Music Player	I	0.43	-0.14
	F3	Voice command	I	0.31	-0.08
	F4	Memory setup	I	0.35	-0.17

Table 8. Results of Cluster Analysis

Cluster	Male (60-69 yrs.)	Male (70-79 yrs.)	Female (60-69 yrs.)	Female (70-79 yrs.)	Attractive (A)	One-dimensional (O)	Must-Be (M)	Indifferent (I)	Reverse (R)
0	10.53%	42.11%	21.05%	26.32%	34.53%	21.89%	18.74%	24.84%	0.00%
1	14.29%	38.10%	14.29%	33.33%	27.62%	25.33%	19.81%	27.05%	0.19%
2	21.74%	34.78%	13.04%	30.43%	29.39%	18.96%	18.26%	32.17%	1.22%

Cluster 0 consists predominantly of older males aged 70–79 years (42.11%) and females aged 70–79 years (26.32%), indicating a strong representation of users in the advanced elderly stage. This cluster demonstrates the highest proportion of Attractive responses (34.53%), suggesting that these users are especially responsive to features that deliver enjoyment, comfort, or an enhanced experience—such as body massage and automatic warm-air drying. Their relatively lower emphasis on Must-be (18.74%) suggests that their satisfaction may not depend solely on basic functionality but rather on emotionally engaging enhancements. The Indifferent rate (24.84%) further suggests that while these users value certain advanced features, they also consider several others as non-essential. Cluster 1 is more evenly distributed across gender and age groups, with a notable proportion of females aged 70–79 years (33.33%) and males aged 70–79 years (38.10%). This group reflects a balanced Kano distribution, with One-dimensional (25.33%) and Indifferent (27.05%) categories slightly dominating. This implies that users in this segment are more performance-oriented—placing value on features that deliver proportional satisfaction but also holding neutral views on many aspects of the system. Their Must-be rate (19.81%) is the highest among the three clusters, reflecting a cautious expectation for basic reliability and functionality. Cluster 2 exhibits the highest percentage of users aged 60–69 years, both male (21.74%) and female (13.04%), and a strong representation of females aged 70–79 years (30.43%). This cluster is particularly defined by a high proportion of Indifferent responses (32.17%), indicating a group that is less responsive to both essential and advanced features. These users may prioritize simplicity and familiarity over innovation, and are likely to reject features that feel unnecessary or overwhelming. Their Reverse response rate (1.22%), although low overall, is the highest among the clusters, potentially signifying some resistance to certain technological elements. Taken together, these findings highlight the heterogeneity of user needs within the elderly population. Segmenting by cluster provides a more nuanced understanding than age or gender alone. For instance, while older males tend to dominate Cluster 0 and prefer appealing, non-essential features, younger seniors in Cluster 2 appear more indifferent or resistant to feature complexity. Such insights are critical for guiding inclusive design, feature prioritization, and marketing strategies in assistive technology for aging populations.

4.4 Heatmap Analysis of Kano Responses by User Cluster

To gain deeper insight into how different user groups perceive and prioritize the features of the Automatic Shower Device for the Elderly, this study employed a heatmap visualization. Heatmaps are particularly effective for displaying patterns of categorical data across multiple dimensions, allowing simultaneous observation of both intensity and distribution. In this analysis, heatmaps were generated for three specific Kano response types—Must-Be (M), Attractive (A), and One-Dimensional (O), as shown in Figure 4, to identify which features were most frequently associated with each type across the clusters derived from K-Means clustering. Each cell in the heatmap represents the frequency count of a particular Kano response (e.g., "Must-Be") for a given feature within a specific cluster, with color gradients indicating the relative intensity of responses. This approach enables a visual, comparative understanding of user expectations, desires, and satisfaction drivers across distinct elderly user segments. By observing the patterns in these heatmaps, design teams and developers can prioritize which features to include, enhance, or simplify to better align with the differentiated needs of target user groups.

Features categorized as Must-Be (M) represent essential expectations that users assume will be included by default. While their presence may not significantly enhance satisfaction, their absence typically results in dissatisfaction. Analysis of the heatmap reveals that across all clusters, "Automatic water temperature control" consistently ranks as a critical Must-Be requirement, underscoring the fundamental importance of thermal safety and comfort among elderly users. Additionally, features such as "Product guarantee" and "Comfortable seat" appear prominently in Clusters 1 and 2, suggesting shared expectations regarding product reliability and ergonomic support. Interestingly, Cluster 2, which consists of a higher proportion of younger elderly individuals (aged 60–69), more frequently designates features such as "Fall Detection" and "Automated emergency call" as Must-Be than Cluster 0. This pattern implies a heightened awareness of safety and emergency preparedness in the early stages of aging. These findings highlight that such core features should be regarded as non-negotiable elements in the product's design and functionality, and must be clearly emphasized in product communication, instructional materials, and marketing strategies. Attractive (A) features are elements that users do not explicitly expect, yet, when present, create a sense of surprise and delight, significantly enhancing user satisfaction. Cluster 0 demonstrates strong preferences for features such as "Body massage," "Shower heads," and "Automatic warm air drying," indicating that this group places high value on spa-like, comfort-enhancing experiences. In contrast, Cluster 1 exhibits a different trend, with a high concentration of Attractive responses for "Ozone therapy" and "Mobile application control," reflecting a more progressive attitude and openness toward innovative or digital features. Meanwhile, Cluster 2 shows a more moderate pattern, with appreciation for basic conveniences like "Easy to set up" and "Voice command," but generally records fewer Attractive responses overall. This may suggest that users in Cluster 2 exhibit lower emotional engagement or enthusiasm for optional or luxurious enhancements. These patterns highlight the importance of Attractive features as key differentiators in design and marketing—particularly for Cluster 0, where such features could be promoted as wellness-oriented or premium add-ons to enhance user appeal and product satisfaction.

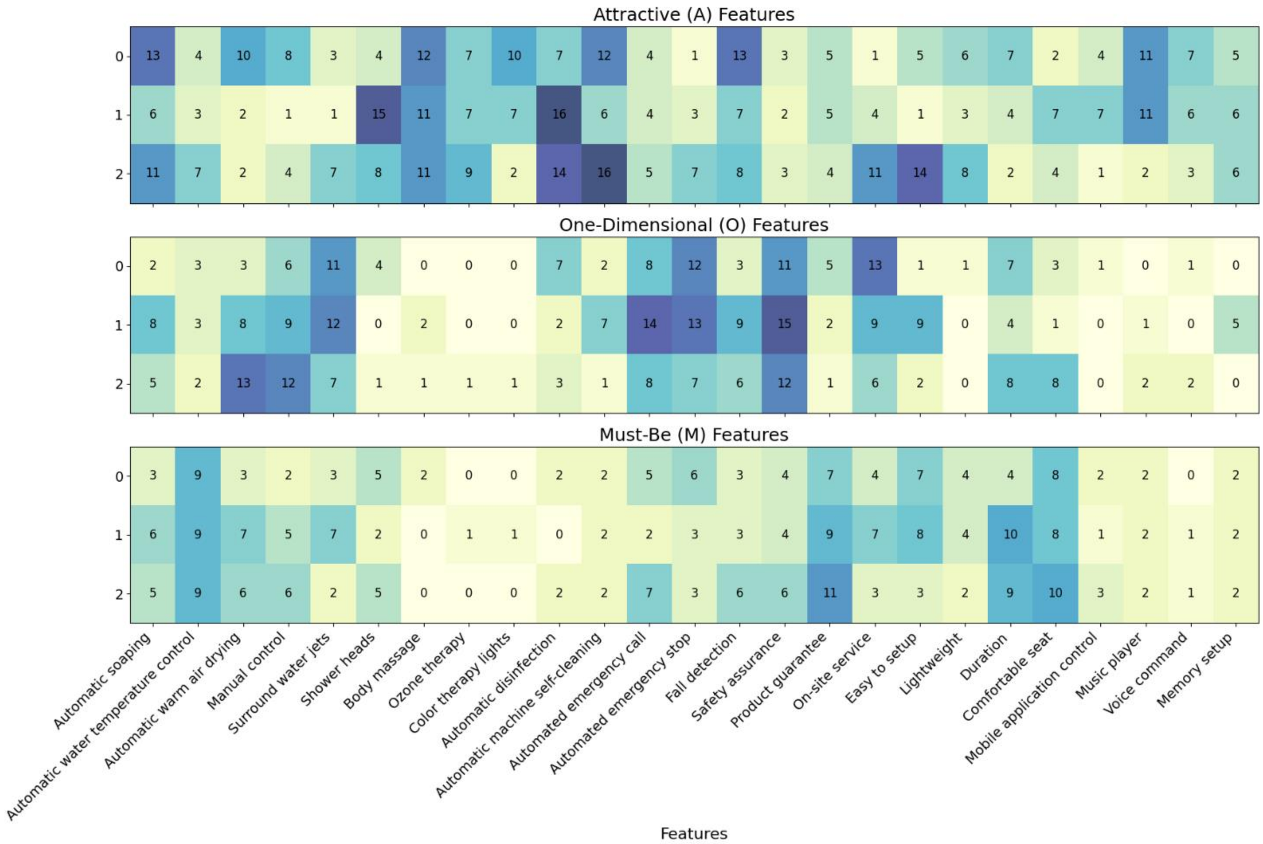

Figure 4. Heatmaps of Attractive (A), One-Dimensional (O), and Must-Be (M) features across user clusters.

One-Dimensional (O) features are those that contribute to user satisfaction in a directly proportional manner—the better these features perform or the more of them are present, the greater the user's satisfaction. As revealed in the heatmap analysis, "Automated emergency stop" and "Fall Detection" are consistently rated highly across Clusters 1 and 2, underscoring their critical role as performance-driven safety functions. Cluster 1, in particular, places considerable emphasis on "Product guarantee" and "On-site service," suggesting that users in this group prioritize dependable service and long-term support as key components of product performance. Meanwhile, Cluster 2 assigns relatively high value to features such as "Manual control" and "Automatic warm air drying," indicating appreciation for hands-on functionality and immediate physical comfort. These results affirm that One-Dimensional features represent a significant avenue for gaining a competitive advantage, as focused enhancements in these areas can translate directly into increased user satisfaction. Prioritizing the performance and reliability of these features can thus yield measurable improvements in product perception and user loyalty. The results of this study are consistent with prior research on assistive technology design, which identifies safety, reliability, and ease of use as key factors influencing elderly user acceptance. Previous studies have emphasized the importance of fall-prevention and emergency-response functions in building trust in assistive systems, particularly in personal care applications [58, 59]. The present findings reinforce these observations by showing that safety and hygiene-related features generate the strongest effects on satisfaction and dissatisfaction [60]. While existing literature often highlights the potential of advanced digital interfaces to enhance engagement, the results indicate that software-based features have limited perceived value compared with fundamental safety and comfort requirements. This highlights the need for user-centered rather than technology-driven design approaches. By combining Kano analysis with clustering techniques, this study contributes a data-driven engineering design framework that complements prior qualitative research and supports systematic feature prioritization in assistive technology development.

4.5 Limitations and Future Research

Despite providing valuable insights into user preferences and satisfaction through the integration of the Kano model and K-Means clustering, this study has several limitations that should be acknowledged. First, the sample size and demographic composition may not fully represent the heterogeneity of the elderly population. Factors such as age subgroups (e.g., early elderly versus advanced elderly), health conditions, and prior experience with assistive technologies were not explicitly modeled as moderating variables, which may limit the generalizability of the findings across broader populations or cultural contexts. Second, the identification of product features was based solely on expert input and did not directly involve elderly users or caregivers at the initial feature generation stage. While expert-driven brainstorming is suitable for early-stage engineering design, the absence of direct end-user participation may limit the completeness of the identified feature set. Future studies should incorporate participatory design approaches, such as co-design workshops or interviews with elderly users and caregivers, to further validate and refine the feature dimensions. Third, this study employed a static Kano model, which assumes that user perceptions remain stable over time. In practice, preferences for assistive technologies may evolve as users gain experience, receive caregiver support, or improve digital literacy. In addition, the use of K-Means clustering introduces methodological constraints, as the algorithm assumes spherical cluster structures and relies on distance-based calculations. Given that Kano categories are categorical in nature and were numerically encoded for clustering, this approach may not fully capture more complex or non-spherical preference patterns. Furthermore, clustering results are sensitive to the predefined number of clusters (k). Although the elbow method and silhouette analysis were used to support the selection of k, the relatively small sample size may still affect cluster stability and reproducibility. Therefore, the clustering results should be interpreted as exploratory rather than definitive population-level segmentation. Future studies may benefit from larger samples and alternative clustering techniques, such as hierarchical clustering or density-based methods (e.g., DBSCAN), to validate or complement the segmentation outcomes. Future research should consider larger, more diverse samples, including elderly users from home care, assisted living, and clinical settings. Longitudinal designs may further reveal how satisfaction and expectations change over time. Additionally, hybrid analytical approaches that combine qualitative methods (e.g., interviews or observations) with quantitative clustering could provide a more comprehensive understanding of user needs. Finally, incorporating adaptive or real-time feedback mechanisms into assistive device design may support dynamic personalization and enhance long-term usability and engagement.

5. Conclusion

This study contributes to an engineering design framework for assistive shower systems by translating user satisfaction data into actionable insights for design and decision-making. By integrating the Kano model with K-Means clustering, the framework enables systematic feature prioritization based on user expectations, safety requirements, and ergonomic considerations. Must-Be attributes such as fall detection, automated emergency call, and emergency stop functions represent fundamental safety constraints. From an engineering design perspective, these features should be embedded as baseline requirements, as their absence directly undermines user trust and system acceptance. One-Dimensional features, including product guarantee and on-site service, emphasize the importance of reliability and lifecycle-oriented design, highlighting the relevance of product–service system thinking in assistive technologies. Attractive features, such as body massage and advanced shower functions, were valued by specific user segments and can be strategically implemented as optional or modular components. This enables cost–performance optimization while accommodating heterogeneous user needs. The clustering results further indicate that younger elderly users prioritize safety-related features, whereas older users place greater emphasis on comfort, reinforcing the need for adaptive and ergonomically scalable design strategies. Notably, software-based features were largely perceived as Indifferent across clusters, suggesting that increased technological complexity does not necessarily translate into higher perceived value. This underscores the importance of aligning digital functions with usability and user capability rather than pursuing technology-driven design. Overall, the proposed engineering design framework demonstrates how Kano-based classification and user segmentation can inform structured decision-making in assistive technology development, supporting safer, more acceptable, and user-centered design solutions for elderly populations.

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References

[1] Harmo, P.; Taipalus, T.; Knuuttila, J.; Vallet, J.; Halme, A. Needs and solutions-home automation and service robots for the elderly and disabled. In *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems*, **2005**; IEEE: pp 3201–3206. https://doi.org/10.1109/IROS.2005.1545387

[2] Marques, B.; McIntosh, J.; Valera, A.; Gaddam, A. Innovative and Assistive eHealth Technologies for Smart Therapeutic and Rehabilitation Outdoor Spaces for the Elderly Demographic. *Multimodal Technol. Interact.* **2020**, *4*(4), 76. https://doi.org/10.3390/mti4040076

[3] Baucas, M. J.; Spachos, P.; Gregori, S. Internet-of-Things Devices and Assistive Technologies for Health Care: Applications, Challenges, and Opportunities. *IEEE Signal Process. Mag.* **2021**, *38*(4), 65–77. https://doi.org/10.1109/MSP.2021.3075929

[4] Brouwer, D. M.; Sadlo, G.; Winding, K.; Hanneman, M. I. G. Limitations in Mobility: Experiences of Visually Impaired Older People. *Br. J. Occup. Ther.* **2008**, *71*(10), 414–421. https://doi.org/10.1177/030802260807101003

[5] Chen, Z.; Yu, J.; Song, Y.; Chui, D. Aging Beijing: Challenges and strategies of health care for the elderly. *Ageing Res. Rev.* **2010**, *9*, S2–S5. https://doi.org/10.1016/j.arr.2010.07.001

[6] Wang, H.-H.; Tsay, S.-F. Elderly and long-term care trends and policy in Taiwan: Challenges and opportunities for health care professionals. *Kaohsiung J. Med. Sci.* **2012**, *28*(9), 465–469. https://doi.org/10.1016/j.kjms.2012.04.002

[7] Subramaniyaswamy, V.; Vijayakumar, V.; Logesh, R.; Indraganti, V. An ontology-driven personalized food recommendation in IoT-based healthcare system. *J. Supercomput.* **2019**, *75*, 3184–3216. https://doi.org/10.1007/s11227-018-2331-8

[8] Wickramasinghe, A.; Torres, R. L. S.; Ranasinghe, D. C. Recognition of falls using dense sensing in an ambient assisted living environment. *Pervasive Mobile Comput.* **2017**, *34*, 14–24. https://doi.org/10.1016/j.pmcj.2016.06.004

[9] Selvaraj, S.; Sundaravaradhan, S. Challenges and opportunities in IoT healthcare systems: a systematic review. *SN Appl. Sci.* **2019**, *2* (1), 139. https://doi.org/10.1007/s42452-019-1925-y

[10] Sixsmith, A. Ethical challenges in aging and technology. Presented at the *15th International Conference on PErvasive Technologies Related to Assistive Environments (PETRA)*, Corfu, Greece, 2022. https://doi.org/10.1145/3529190.3534756

[11] Sixsmith, A. AgeTech: Technology-based solutions for aging societies. In *Promoting the health of older adults: the Canadian experience*; 2021; pp 135–151

[12] Morato, J.; Sanchez-Cuadrado, S.; Iglesias, A.; Campillo, A.; Fernández-Panadero, C. Sustainable Technologies for Older Adults. *Sustainability* **2021**, *13*(15), 8465. https://doi.org/10.3390/su13158465

[13] Haescher, M.; Höpfner, F.; Jähne-Raden, N.; Denker, K.; Koldrack, P.; Rostalski, P.; Kirste, T.; Bieber, G. Automated fall risk assessment of elderly using wearable devices. *J. Rehabil. Assist. Technol. Eng.* **2020**, *7*, 2055668320946209. https://doi.org/10.1177/2055668320946209

[14] Perez, A. J.; Siddiqui, F.; Zeadally, S.; Lane, D. A review of IoT systems to enable independence for the elderly and disabled individuals. *Internet Things* **2023**, *21*, 100653. https://doi.org/10.1016/j.iot.2022.100653

[15] Ramkumar, J.; Karthikeyan, C.; Vamsidhar, E.; Dattatraya, K. N. Automated pill dispenser application based on IoT for patient medication. In *IoT and ICT for Healthcare Applications*; Springer: **2020**; pp 231–253. https://doi.org/10.1007/978-3-030-42934-8_13

[16] Fernandes, N.; Amorim, A. R.; Silva, B.; Freitas, J.; Mendonça, J. P. TAB-Med: automated pill dispenser in residential environments. In *Innovations in Mechanical Engineering*; Springer: **2022**; pp 359–370. https://doi.org/10.1007/978-3-030-79165-0_34

[17] Maswadi, K.; Ghani, N. B. A.; Hamid, S. B. Systematic Literature Review of Smart Home Monitoring Technologies Based on IoT for the Elderly. *IEEE Access* **2020**, *8*, 92244–92261. https://doi.org/10.1109/ACCESS.2020.2992727

[18] Sokullu, R.; Akkaş, M. A.; Demir, E. IoT supported smart home for the elderly. *Internet Things* **2020**, *11*, 100239. https://doi.org/10.1016/j.iot.2020.100239

[19] Boumpa, E.; Kakarountas, A. Home supporting smart systems for elderly people. In *Convergence of ICT and Smart Devices for Emerging Applications*; Springer: 2020; pp 81–98. https://doi.org/10.1007/978-3-030-41368-2_4

[20] Salichs, M. A.; Castro-González, Á.; Salichs, E.; Fernández-Rodríguez, R.; Maroto-Gómez, M.; Gamboa-Montero, J. J.; Marques-Villarroya, S.; Castillo, J. C.; Alonso-Martín, F.; Malfaz, M. Mini: A New Social Robot for the Elderly. *Int. J. Soc. Rob.* **2020**, *12*(6), 1231–1249. https://doi.org/10.1007/s12369-020-00687-0

[21] de Barcelos Silva, A.; Gomes, M. M.; da Costa, C. A.; da Rosa Righi, R.; Barbosa, J. L. V.; Pessin, G.; De Paz, G. F.; Jose, V. R. Q. Intelligent personal assistants: A systematic literature review. *Expert Syst. Appl.* **2020**, *147*, 113193. https://doi.org/10.1016/j.eswa.2020.113193

[22] Fong, J. H.; Mitchell, O. S.; Koh, B. S. Disaggregating activities of daily living limitations for predicting nursing home admission. *Health Serv. Res.* **2015**, *50*(2), 560–578. https://doi.org/10.1111/1475-6773.12235

[23] Millán-Calenti, J. C.; Tubío, J.; Pita-Fernández, S.; González-Abraldes, I.; Lorenzo, T.; Fernández-Arruty, T.; Maseda, A. Prevalence of functional disability in activities of daily living (ADL), instrumental activities of daily living (IADL) and associated factors, as predictors of morbidity and mortality. *Arch. Gerontol. Geriatr.* **2010**, *50*(3), 306–310. https://doi.org/10.1016/j.archger.2009.04.017

[24] Golding-Day, M.; Whitehead, P.; Radford, K.; Walker, M. Interventions to reduce dependency in bathing in community dwelling older adults: a systematic review. *Syst. Rev.* **2017**, *6*, 1–6. https://doi.org/10.1186/s13643-017-0586-4

[25] Wang, W.; Chen, Y.; Zou, X.; Wang, S.; Ferreira, J. P.; Liu, T. Development of Bath Auxiliary Robot for the Disabled Elderly. In *2021 IEEE International Conference on Intelligence and Safety for Robotics (ISR)*, **2021**; pp 85–88. https://doi.org/10.1109/ISR50024.2021.9419499

[26] Zlatintsi, A.; Dometios, A. C.; Kardaris, N.; Rodomagoulakis, I.; Koutras, P.; Papageorgiou, X.; Maragos, P.; Asfour, T.; Lichtenthäler, R.; Reiser, U.; et al. I-Support: A robotic platform of an assistive bathing robot for the elderly population. *Robotics Auton. Syst.* **2020**, *126*, 103451. https://doi.org/10.1016/j.robot.2020.103451

[27] Wenninger, A.; Rau, D.; Röglinger, M. Improving customer satisfaction in proactive service design. *Electron. Mark.* **2022**, *32*(3), 1399–1418. https://doi.org/10.1007/s12525-022-00565-9

[28] Xi, L.; Zhang, H.; Li, S.; Cheng, J. Integrating fuzzy Kano model and fuzzy importance-performance analysis to analyse the attractive factors of new products. *Int. J. Distrib. Sens. Netw.* **2020**, *16*(5), 1550147720920222. https://doi.org/10.1177/1550147720920222

[29] Zhao, S.; Zhang, Q.; Peng, Z.; Fan, Y. Integrating customer requirements into customized product configuration design based on Kano's model. *J. Intell. Manuf.* **2020**, *31*(3), 597–613. https://doi.org/10.1007/s10845-019-01467-y

[30] Kohli, A.; Singh, R. An assessment of customers' satisfaction for emerging technologies in passenger cars using Kano model. *Vilakshan-XIMB J. Manag.* **2021**, *18*(1), 76–88. https://doi.org/10.1108/XJM-08-2020-0103

[31] Lu, M.-T.; Lu, H.-P.; Chen, C.-S. Exploring the Key Priority Development Projects of Smart Transportation for Sustainability: Using Kano Model. *Sustainability* **2022**, *14*(15), 9319. https://doi.org/10.3390/su14159319

[32] Yang, Y.; Li, Q.; Li, C.; Qin, Q. User requirements analysis of new energy vehicles based on improved Kano model. *Energy* **2024**, *309*, 133134. https://doi.org/10.1016/j.energy.2024.133134

[33] Wang, T.; Wang, W.; Feng, J.; Fan, X.; Guo, J.; Lei, J. A novel user-generated content-driven and Kano model focused framework to explore the impact mechanism of continuance intention to use mobile APPs. *Comput. Hum. Behav.* **2024**, *157*, 108252. https://doi.org/10.1016/j.chb.2024.108252

[34] Cavacece, Y.; Maggiore, G.; Resciniti, R.; Moretta Tartaglione, A. Evaluating digital health attributes for users' satisfaction: an application of the Kano model. *TQM J.* **2025**, *37*(3), 831–852. https://doi.org/10.1108/TQM-09-2023-0301

[35] Li, Z.-Q.; Cao, G.-P.; Cai, S.-Y.; Wang, D.-Y.; Zhang, X.-C. Functional requirements and design strategy of E-sports chair based on the KANO model. *BioResources* **2024**, *19*(3), 4679–4697. https://doi.org/10.15376/biores.19.3.4679-4697

[36] Tabianan, K.; Velu, S.; Ravi, V. K-means clustering approach for intelligent customer segmentation using customer purchase behavior data. *Sustainability* **2022**, *14*(12), 7243. https://doi.org/10.3390/su14127243

[37] Chiu, C.-Y.; Chen, Y.-F.; Kuo, I.-T.; Ku, H. C. An intelligent market segmentation system using k-means and particle swarm optimization. *Expert Syst. Appl.* **2009**, *36*(3), 4558–4565. https://doi.org/10.1016/j.eswa.2008.05.029

[38] Chen, Y.; Tan, P.; Li, M.; Yin, H.; Tang, R. K-means clustering method based on nearest-neighbor density matrix for customer electricity behavior analysis. *Int. J. Electr. Power Energy Syst.* **2024**, *161*, 110165. https://doi.org/10.1016/j.ijepes.2024.110165

[39] Zhao, H.-H.; Luo, X.-C.; Ma, R.; Lu, X. An extended regularized K-means clustering approach for high-dimensional customer segmentation with correlated variables. *IEEE Access* **2021**, *9*, 48405–48412. https://doi.org/10.1109/ACCESS.2021.3067499

[40] Fang, C.; Liu, H. Research and application of improved clustering algorithm in retail customer classification. *Symmetry* **2021**, *13*(10), 1789. https://doi.org/10.3390/sym13101789

[41] Yin, S.; Cai, X.; Wang, Z.; Zhang, Y.; Luo, S.; Ma, J. Impact of gamification elements on user satisfaction in health and fitness applications: A comprehensive approach based on the Kano model. *Comput. Hum. Behav.* **2022**, *128*, 107106. https://doi.org/10.1016/j.chb.2021.107106

[42] Jin, J.; Jia, D.; Chen, K. Mining online reviews with a Kansei-integrated Kano model for innovative product design. *Int. J. Prod. Res.* **2022**, *60*(22), 6708–6727. https://doi.org/10.1080/00207543.2021.1949641

[43] He, C.; Li, Z.; Liu, D.; Zou, G.; Wang, S. Improving the functional performances for product family by mining online reviews. *J. Intell. Manuf.* **2023**, *34*(6), 2809–2824. https://doi.org/10.1007/s10845-022-01961-w

[44] Pandey, A.; Sahu, R.; Joshi, Y. Kano Model Application in the Tourism Industry: A Systematic Literature Review. *J. Qual. Assur. Hosp. Tour.* **2022**, *23*(1), 1–31. https://doi.org/10.1080/1528008X.2020.1839995

[45] Shi, Y.; Peng, Q. Enhanced customer requirement classification for product design using big data and improved Kano model. *Adv. Eng. Inf.* **2021**, *49*, 101340. https://doi.org/10.1016/j.aei.2021.101340

[46] Dou, R.; Zhang, Y.; Nan, G. Application of combined Kano model and interactive genetic algorithm for product customization. *J. Intell. Manuf.* **2019**, *30*, 2587–2602. https://doi.org/10.1007/s10845-016-1280-4

[47] Fofan, A. C.; Oliveira, L. A. B.; Melo, F. J. C.; Jerônimo, T. B.; Medeiros, D. D. An Integrated Methodology Using PROMETHEE and Kano's Model to Rank Strategic Decisions. *Eng. Manage. J.* **2019**, *31*(4), 270–283. https://doi.org/10.1080/10429247.2019.1655351

[48] Shen, Y.; Kokkranikal, J.; Christensen, C. P.; Morrison, A. M. Perceived importance of and satisfaction with marina attributes in sailing tourism experiences: A kano model approach. *J. Outdoor Recreat. Tour.* **2021**, *35*, 100402. https://doi.org/10.1016/j.jort.2021.100402

[49] Cai, M.; Wu, M.; Luo, X.; Wang, Q.; Zhang, Z.; Ji, Z. Integrated framework of Kansei engineering and Kano model applied to service design. *Int. J. Hum.–Comput. Interact.* **2023**, *39*(5), 1096–1110. https://doi.org/10.1080/10447318.2022.2102301

[50] Tang, L.-L.; Chen, S.-H.; Lin, C.-C. Integrating FMEA and the Kano Model to Improve the Service Quality of Logistics Centers. *Processes* **2021**, *9*(1), 51. https://doi.org/10.3390/pr9010051

[51] Bhardwaj, J.; Yadav, A.; Chauhan, M. S.; Chauhan, A. S. Kano model analysis for enhancing customer satisfaction of an automotive product for Indian market. *Mater. Today: Proc.* **2021**, *46*, 10996–11001. https://doi.org/10.1016/j.matpr.2021.02.093

[52] Madzík, P.; Budaj, P.; Mikuláš, D.; Zimon, D. Application of the Kano Model for a Better Understanding of Customer Requirements in Higher Education-A Pilot Study. *Adm. Sci.* **2019**, *9*(1), 11. https://doi.org/10.3390/admsci9010011

[53] Ma, M.-Y.; Chen, C.-W.; Chang, Y.-M. Using Kano model to differentiate between future vehicle-driving services. *Int. J. Ind. Ergon.* **2019**, *69*, 142–152. https://doi.org/10.1016/j.ergon.2018.11.003

[54] Palumbo, F. Developing a new service for the digital traveler satisfaction: The Smart Tourist App. *Int. J. Digit. Account. Res.* **2015**, *15*. https://doi.org/10.4192/1577-8517-15_2

[55] Violante, M. G.; Vezzetti, E. Kano qualitative vs quantitative approaches: An assessment framework for products attributes analysis. *Comput. Ind.* **2017**, *86*, 15–25. https://doi.org/10.1016/j.compind.2016.12.007

[56] Minh, H.-L.; Sang-To, T.; Wahab, M. A.; Cuong-Le, T. A new metaheuristic optimization based on K-means clustering algorithm and its application to structural damage identification. *Knowl.-Based Syst.* **2022**, *251*, 109189. https://doi.org/10.1016/j.knosys.2022.109189

[57] Elshaaer, N. I.; Elsayed, S. F. Improving Spa Services to a Better Customers' Attraction (A Case Study on Red Sea Resorts). *J. Assoc. Arab Univ. Tour. Hosp.* **2016**, *13*(1), 167–182. https://doi.org/10.21608/jaauth.2016.49970

[58] Friedrich, P.; Schmid, S.; Fuchs, D. Acceptance of assistive fall prevention technologies: an online survey. *Procedia Comput. Sci.* **2024**, *246*, 4582–4591. https://doi.org/10.1016/j.procs.2024.09.322

[59] Nyrop, K. A.; Zimmerman, S.; Sloane, P. D.; Bangdiwala, S. Fall prevention and monitoring of assisted living patients: an exploratory study of physician perspectives. *J. Am. Med. Dir. Assoc.* **2012**, *13*(5), 429–433. https://doi.org/10.1016/j.jamda.2011.08.003

[60] Li, J.; Mo, Y.; Jiang, S.; Ma, L.; Zhang, Y.; Wei, S. Bathing assistive devices and robots for the elderly. *Biomimetic Intell. Rob.* **2025**, 100218. https://doi.org/10.1016/j.birob.2025.100218