Design of Multi-Functional Dining Tables for an Accessible Dining Experience

Yousheng Yao,[a,b,*] Yuanhao Ding,[a] Tiantian Sun,[a] Junpeng Zheng,[a,c] Shuangyi He,[a] Hao Gu,[a] Junfeng Chen,[a] and Hongchen Li[a]

Traditional dining tables often lack adjustability in height, legroom, and operability for wheelchair users and disabled older adults, thereby limiting their suitability in accessible dining contexts. This study proposes and evaluates three multifunctional dining table concepts tailored to diverse physical abilities. Field observations of home mealtime routines were conducted, user-journey maps were developed, and affinity diagramming was applied to synthesize requirements. Principal Component Analysis (PCA) reduced the dimensionality of the requirements and revealed latent factors shaping the accessible dining experience. Order Relation Analysis (ORA) and the Criteria Importance Through Intercriteria Correlation (CRITIC) method were used to derive combined subjective and objective indicator weights that informed the design specifications. Three wheelchair compatible prototypes were generated and comparatively assessed, and the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) identified the top-performing concept. Results indicated improvements in functional reach, operational convenience, and dining safety relative to conventional tables. The study provides a replicable workflow that integrates user research with multi-criteria decision making for accessible furniture design. Future work will embed sensing and actuation to enhance automation and adaptability, facilitating broader deployment in universal design.

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*Contact information: a: Hexiangning College of Art and Design, Zhongkai University of Agriculture and Engineering, Guangzhou, 510000 China; b: Humanities Institute of the Arts, Macau University of Science and Tech nology, Macau 999078 China; c: Agricultural Development Promotion Association of Jiangdong Town, Chaozhou 510000 China; *Corresponding author: raoyousheng@zhku.edu.cn*

INTRODUCTION

With population aging and growing social attention to equity and inclusion, accessible and universal design have become priorities in contemporary furniture design (Gupta *et al.* 2025). Accessible design has emerged as a central topic across the design disciplines (Patrick and Hollenbeck 2021). Cho *et al.* (2016) argue that conventional dining tables are largely static systems with fixed geometry and limited adjustability, which constrains use in small dwellings and for people with mobility impairments. In parallel, Nageb Fewella (2024) introduces behavior-smart furniture that integrates technology with affective interaction, outlining a three-part framework of behavior, technology, and emotion that can yield low-cost, easy-to-implement interactive solutions. However, the specific problem of designing dining tables that accommodate diverse abilities remains under addressed by systematic, multi-criteria methods that connect user research to engineering decisions.

This study targeted a multifunctional dining table system for older adults with disabilities and wheelchair users. The objectives were to: (1) identify priority needs and constraints during mealtime in homes and nursing facilities through user requirement analysis; (2) develop three design concepts that combine functional modules, behavior-informed interactions, and structural innovations, guided by the ranked importance of need indicators; (3) evaluate and select the optimal concept using multi-criteria decision analysis and verify its compliance with relevant human-machine and ergonomic standards.

To achieve these aims, the authors adopted a mixed-method analytical workflow that links qualitative inquiry with quantitative weighting and decision making. User-journey mapping was used to capture high-frequency pain points and emotional fluctuation nodes across dining stages. Affinity diagram (AD) synthesizes user needs and clarifies the design direction. Principal Component Analysis (PCA) reduces data dimensionality and reveals key latent factors, which in turn structure the evaluation indicator system. Order Relation Analysis (ORA) elicits expert judgments from eight specialists to derive subjective weights, while the Criteria Importance Through Intercriteria Correlation (CRITIC) method provides objective weights from the data. The integrated weights guide the development of three wheelchair-compatible prototypes. The Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS) identifies the optimal concept, which is then examined through ergonomic verification to confirm alignment with anthropometric, reach, and operability requirements for older adults with disabilities.

LITERATURE REVIEW

Accessible and Aging-Friendly Design

Accessible furniture has become a salient topic in contemporary furniture design, as demand grows among older adults and people with disabilities. Integrating accessibility principles into high-use furniture, including dining tables, is a shared concern of research and practice. Zhang *et al.* (2025) developed a user-designer cognitive synergy framework that combines grounded theory, the fuzzy Kano models, and the DEMATEL method to translate aging-friendly needs in rural public spaces into actionable strategies and to evaluate their effectiveness. Patil and Raghani (2025) used a mixed-method approach to specify accessible interior principles, integrating multi-sensory cues and modular layouts and validating benefits for users with visual impairments while identifying policy gaps. Zhou *et al.* (2022) applied questionnaires and Analytical Hierarchy Process (AHP) to locate sofa-use pain points for older users, captured skeletal key points with Kinect during sit-to-stand transitions, computed joint angles, and used a neural-network analysis in SPSS to determine influential angles, culminating in an aging-friendly smart-sofa prototype. In product-level studies, Yu *et al.* (2025) modeled core needs for air-pressure massage cushions and converted them into technical parameters and key design elements, optimizing feasibility through JACK simulation. Zhang *et al.* (2025) examined links between furniture and elder well-being and used a convolutional neural network to analyze posture for aging-friendly support strategies. In kitchen scenarios, Zhou *et al.* (2024) combined surveys, fieldwork, and interviews with OpenPose and REBA assessments to study object-retrieval behaviors of 42 independently living older adults, identify stagespecific risks, and joint-angle differences, and propose a comfort-gradient model to guide cabinet and furniture design.

Despite these advances, most studies have addressed spatial layouts or specific objects, such as sofas and massage cushions, rather than dining tables, which are central to daily living. Existing approaches also tend to privilege a single evaluation dimension and underrepresent the heterogeneity of disability, limiting the transferability of results to multifunctional dining furniture. There remains a need for systematic frameworks that integrate user research with multi-criteria weighting and ergonomics to support wheelchair compatibility, reach, and safe operability in compact homes.

User Needs and Decision Making

A rigorous understanding of target users is foundational to accessible furniture design, particularly for older adults with disabilities. Multifunctional dining tables must meet functional requirements while ensuring comfort, safety, and independence. Fu *et al.* (2025) improved furniture optimization by coupling web-crawler data with an enhanced Kano model to capture user satisfaction. Wang *et al.* (2025) used affinity diagramming to collect emotional vocabulary for Chinese furniture, combined AHP with entropy weighting to obtain indicator weights, applied the CCD method to select core affective terms, and mapped cultural symbols from the Haihun Marquis artifacts to emotions through QFD to refine chair elements. Yu *et al.* (2024) constructed a hierarchical model of children's-furniture needs grounded in emotional design, calculated factor weights with AHP, and selected optimal solutions with TOPSIS. Chang *et al.* (2025) extracted regional symbols from Dayangyu Jiao-tie marbled porcelain, converted user needs with a fuzzy Kano model, and used DEMATEL to reveal causal structures and determine weights for public seating, verifying cultural integration in use.

However, two gaps persist. First, indicator weighting often relies exclusively on either subjective or objective methods, which can introduce bias or neglect data-driven variability. Second, qualitative elicitation of needs is frequently limited, risking sampling and interpretation bias. Addressing these issues for accessible dining, this study elicited needs *via* affinity diagramming, applied principal component analysis for dimensionality reduction and factor structuring, derived subjective weights through Order Relation Analysis with eight experts, and obtained objective weights with the CRITIC method. The integrated weights guide three concept designs for wheelchair-compatible dining tables. Using TOPSIS, the optimal concept was identified and then ergonomic verification conducted against anthropometric, reach, and operability requirements to ensure fitness for use.

METHODOLOGY

Proposed Framework

This study aimed to design a multifunctional dining table that improves the dining experience of older adults with disabilities. a mixed-method workflow combining AD, PCA, ORA, CRITIC, and TOPSIS to was employed to identify, weight, and prioritize user needs, guide concept generation, and select the optimal design. The framework comprises four stages: user-needs elicitation and structuring, indicator weighting, concept development and selection, and ergonomic verification. Figure 1 outlines the workflow.

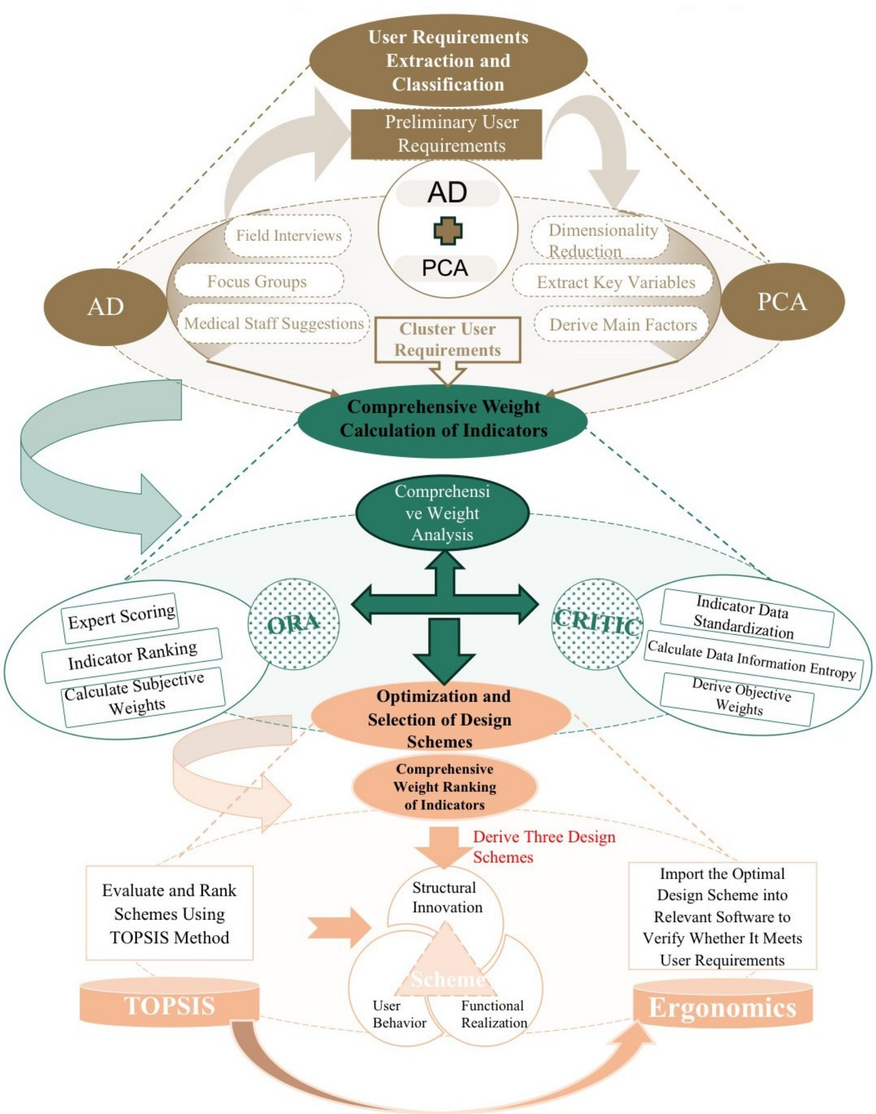

Fig. 1. Design methodology flowchart

- User-needs elicitation and structuring: Guided by user-journey mapping, pre-meal preparation, eating, and post-meal activities were examined to locate high-frequency pain points and emotional fluctuations. The AD method was then used to cluster needs into functional, convenience, safety, and psychological-comfort categories, forming a preliminary indicator set. The data were standardized, and PCA extracted the main components and revealed latent factors shaping the dining experience, which informed the evaluation-indicator framework.
- Based on the indicator system, experts in furniture design, Age-Friendly Design, and accessibility were invited to score the indicators. The ORA yielded subjective weights, while the CRITIC method produced objective weights using the indicators' dispersion and intercorrelation. The two were integrated to obtain comprehensive weights and a ranked list of demand indicators.
- Guided by the comprehensive weights, three dining-table concepts were generated, considering structural innovation, functional modules, and behavior-informed operability. A decision matrix was constructed, and TOPSIS was used to compute

each concept's closeness to the ideal and negative-ideal solutions, supporting multi-attribute ranking and selection of the top-performing design.

- The selected concept was imported into Siemens Jack software for human–machine ergonomic analysis. Representative tasks and postures were simulated to assess wheelchair approach and clearance, reach envelopes, force and operability, and alignment with relevant anthropometric and ergonomic criteria for older adults with disabilities. Findings informed minor adjustments to ensure feasibility and safe, comfortable use.

Affinity Diagram (A) Method

The AD method, also known as the KJ method, which was developed by Jiro Kawakita, supports team-based clustering of fragmented information during ideation and problem structuring (Widjaja and Takahashi 2016). Ideas, observations, problems, or data statements are written on individual cards, grouped by similarity and underlying relations, and labeled with concise category titles to form a hierarchical structure (Lisle *et al.* 2020). In this study, affinity diagramming was used to systematize user needs for accessible multifunctional dining tables. Guided by user-journey maps, semi-structured interviews, and questionnaires, pain points across pre-meal preparation, eating, and post-meal activities were captured among older adults with disabilities. Each item was carded and clustered by similarity and logic to produce categories for functionality, convenience, safety, and psychological comfort, as shown in Fig. 2.

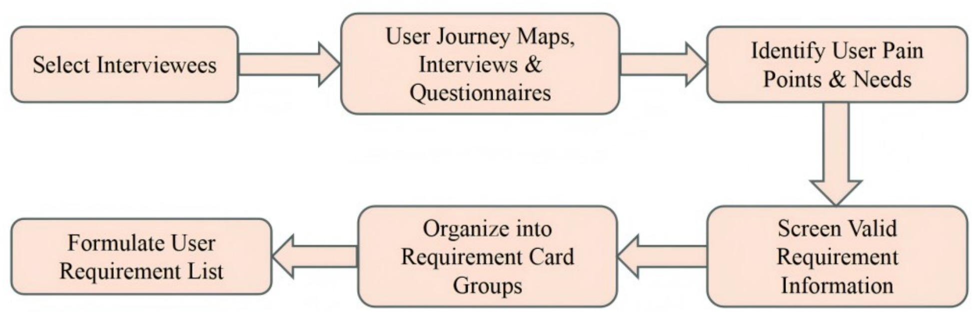

Fig. 2. Affinity diagram information integration process

Principal Component Analysis

The PCA reduces the dimensionality of multivariate data while retaining as much variance as possible (Lui and Lee 2023). The PCA linearly transforms the original variables into uncorrelated principal components ranked by explained variance, thereby revealing the factors that most influence overall variability. In this study, PCA was applied to the demand indicators derived from affinity diagramming. Through extracting principal components, latent factors shaping the accessible dining experience were identified and a quantitative grouping of needs through the loading patterns was achieved. The resulting factors provided a structured basis for constructing the evaluation-indicator system and informed subsequent weighting and concept generation.

Order Relation Analysis Method

Order Relation Analysis is a multi-indicator evaluation method that derives relative importance weights through expert ordering without constructing a full pairwise-judgment matrix. Unlike AHP, ORA compares adjacent indicators in a ranked list, which simplifies the computation and improves consistency. In this study, ORA provided subjective weights for the evaluation indicators. Experts in furniture, aging-friendly design, and accessibility ranked the indicators produced after PCA and supplied adjacent-importance ratios according to Table 1.

(1) To determine the order relation: Assume there are n demand indicators screened through on-site interviews and questionnaire analysis, denoted as $x_1, x_2, \ldots, x_m$. The overall order relation of each demand indicator is established through discussions by the relevant expert group,

$$x_1^* \geq x_2^* \geq \cdots \geq x_k^* \tag{1}$$

where $\boldsymbol{x_k^*}$ represents the k-th ranked demand indicator.

(2) To determine the relative importance of weights of adjacent indicators: For two adjacent demand indicators x_{k-1} and x_k, the relevant experts judge the ratio of their importance,

$$\frac{w_{k-1}}{w_k} = r_k \tag{2}$$

where the value of r_k refers to Table 1.

Table 1. Reference Table for $\boldsymbol{r_k}$ Assignment

r_k	Explanation
1.0	The two demand indicators are of equal importance
1.2	The former is slightly more important than the latter
1.4	The former is significantly more important than the latter
1.6	The former is strongly more important than the latter
1.8	The former is extremely more important than the latter

(3) To calculate the weight system: Based on the r_k values given by experts, first calculate the weight w_m of the last-ranked demand indicator:

$$w_m = (1 + \textstyle\sum_{k=2}^{m} \cdot \prod_{i=k}^{m} \cdot r_i)^{-1} \tag{3}$$

Then, recursively calculate the weights of the remaining demand indicators according to Eq. 4:

$$w_{k-1} = r_k \cdot w_k (k = m, m-1, \ldots, 2) \tag{4}$$

(4) To obtain the weight ranking of demand indicators: Through the above calculations, the weight vector of all demand indicators is obtained:

$$W = (w_1, w_2, \ldots, w_m) \tag{5}$$

(5) Normalize the final weights: Obtain the weights of each demand indicator and their priority ranking.

$$\textstyle\sum_{j=1}^{m} \cdot w_j = 1 \tag{6}$$

CRITIC Method

The CRITIC method assigns objective indicator weights by combining contrast intensity and inter-indicator conflict, thereby reflecting the intrinsic information of the data (Ren and Qu 2024). In this study, CRITIC was used to compute objective weights for the indicator system.

(1) Standardize the data: Standardize the original evaluation matrix $X = (x_{ij})_{n\times m}$ to eliminate the influence of different dimensions of the demand indicators,

$$z_{ij} = \frac{x_{ij}-\overline{x}_j}{s_j} \tag{7}$$

where $\overline{x}_j$ is the mean value of the j-th demand indicator, and s_j is the standard deviation.

(2) Calculate the contrast intensity: The contrast intensity reflects the difference of indicators and is represented by the standard deviation:

$$S_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (z_{ij} - \overline{z}_j)^2} \tag{8}$$

(3) Calculate the conflict: The conflict is represented by the correlation ordinal (Pearson correlation coefficient) between demand indicators:

$$r_{jk} = \frac{\sum_{i=1}^{n} (z_{ij}-\overline{z}_j)(z_{ik}-\overline{z}_k)}{\sqrt{\sum_{i=1}^{n} (z_{ij}-\overline{z}_j)^2}\cdot\sqrt{\sum_{i=1}^{n} (z_{ik}-\overline{z}_k)^2}} \tag{9}$$

If an indicator has a low correlation with other indicators, it indicates that the indicator contains more independent information.

(4) Calculate the information amount: The information amount of indicator j is determined comprehensively by its contrast intensity and conflict:

$$C_j = S_j \cdot \sum_{k=1}^{m} (1 - r_{jk}) \tag{10}$$

(5) Determine the weights: Normalize the information amount of each indicator to obtain the final objective weights:

$$w_j^c = \frac{C_j}{\sum_{j=1}^{m} C_j}, \sum_{j=1}^{m} w_j^c = 1 \tag{11}$$

For the CRITIC weighting method, the weights are mainly determined by two aspects: standard deviation and correlation coefficient. When the standard deviation remains unchanged, the smaller the correlation coefficient, the greater the conflict between indicators, and the greater the weight; when the correlation coefficient is fixed, the larger the standard deviation, the stronger the variability between indicators, and the greater the weight.

TOPSIS Method

The TOPSIS method is a multi-attribute decision method that ranks alternatives by their relative closeness to an ideal solution (Lin *et al.* 2008). It constructs a weighted, normalized decision matrix, determines the positive-ideal and negative-ideal values for each indicator, and computes the distance of each alternative to these ideals. The optimal alternative is closest to the positive ideal and farthest from the negative ideal. In this study, three design concepts were evaluated using TOPSIS based on the integrated indicator weights obtained from the ORA and CRITIC procedures.

(1) Construct the decision matrix: Assume there are m alternative design schemes and n demand evaluation indicators, and construct the decision matrix X,

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{12}$$

where x_{ij} represents the performance of the i-th design scheme under the j-th demand indicator.

(2) Standardize the decision matrix: To eliminate the influence of different dimensions of indicators, standardize the decision matrix,

$$z_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, j = 1,2, \ldots, n \tag{13}$$

where z_{ij} is the element of the standardized matrix.

(3) Construct the weighted standardized decision matrix: Combine the comprehensive weights w_j obtained by the ORA-CRITIC method with the standardized matrix to obtain the weighted standardized decision matrix V:

$$v_{ij} = w_j \cdot z_{ij}, j = 1,2, \ldots, n \tag{14}$$

(4) Determine the positive ideal solution and negative ideal solution: Calculate the positive ideal solution A^+ and negative ideal solution A^-,

$$A^+ = (* \, max_i(v_{ij})), A^- = (* \, min_i(v_{ij})) \tag{15}$$

where A^+ is the maximum value of each indicator, and A^- is the minimum value of each indicator.

(5) Calculate the distance from each scheme to the ideal solution and negative ideal solution: Calculate the Euclidean distance from each scheme to the positive ideal solution and negative ideal solution:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^+)^2}, D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^-)^2} \tag{16}$$

where D_i^+ represents the distance from the i-th scheme to the positive ideal solution, and D_i^- represents the distance from the i-th scheme to the negative ideal solution.

(6) Calculate the relative proximity: Measure the advantages of each design scheme by calculating the relative proximity C_i of each design scheme,

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{17}$$

where a value of C_i closer to 1 indicates that the scheme is closer to the positive ideal solution, *i.e.*, the design scheme is better; a value of C_i closer to 0 indicates that the scheme is closer to the negative ideal solution, *i.e.*, the design scheme is worse.

(7) Rank the design schemes: Rank the schemes according to the relative proximity C_i, and obtain the optimal scheme. The highest C_i corresponds to the optimal scheme, and so on.

CASE STUDY

User-journey Mapping

User needs are the expectations and requirements that people articulate to achieve goals or solve problems within a specific context (Lindgaard *et al.* 2006). In this study, on-site interviews were conducted to document the full dining process of older adults with disabilities in residential care facilities. Key stages and events were identified and visualized in a user-journey map (Fig. 3). Pain points included limited height adjustability of the table and transfer difficulty during pre-meal preparation; suboptimal sitting posture, cumbersome operational steps, and constrained reach during eating; and post-meal challenges such as difficult tabletop cleaning, insufficient under-table clearance that hinders egress, and inefficient tableware collection. The map provides an intuitive overview of preliminary needs and informed subsequent synthesis using the AD method.

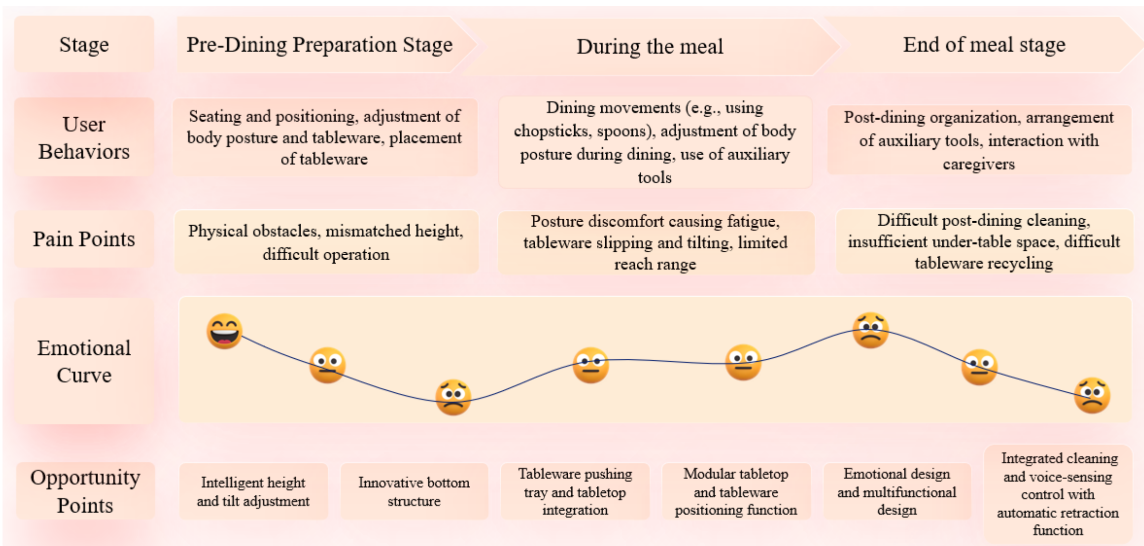

Fig. 3. User journey map

Synthesis of User Needs

Building on pain points and opportunity areas from the user-journey map, design requirements for an accessible multifunctional dining table were consolidated. The AD was used to collect and structure factors related to the dining experience for the target user group. To enhance objectivity, sixteen participants contributed data through on-site interviews, questionnaires, focus groups, and semi-structured interviews, including three university scholars in accessible design, three furniture designers, four undergraduate product-design students, three older adults, and three wheelchair users. To ensure a balanced representation of theoretical knowledge and practical experience, the sample was stratified into expert and user groups. Specifically, the expert participants (scholars and designers) possessed specialized knowledge in accessible design and over three years of industry experience, while the senior students contributed theoretical user-centered design perspectives. Regarding the target users, the older adults were aged between 60 and 80 with typical age-related functional declines (*e.g.*, reduced muscle strength), whereas the wheelchair users had lower-limb impairments but retained the full upper-limb function and cognitive clarity necessary to articulate their needs. All raw statements were grouped and normalized; similar items were merged to ensure completeness and avoid duplication. This process yielded thirty-seven distinct statements that were synthesized into thirteen user-indicator needs (Fig. 4). These indicators provided the basis for dimensionality reduction and classification with PCA in the next step.

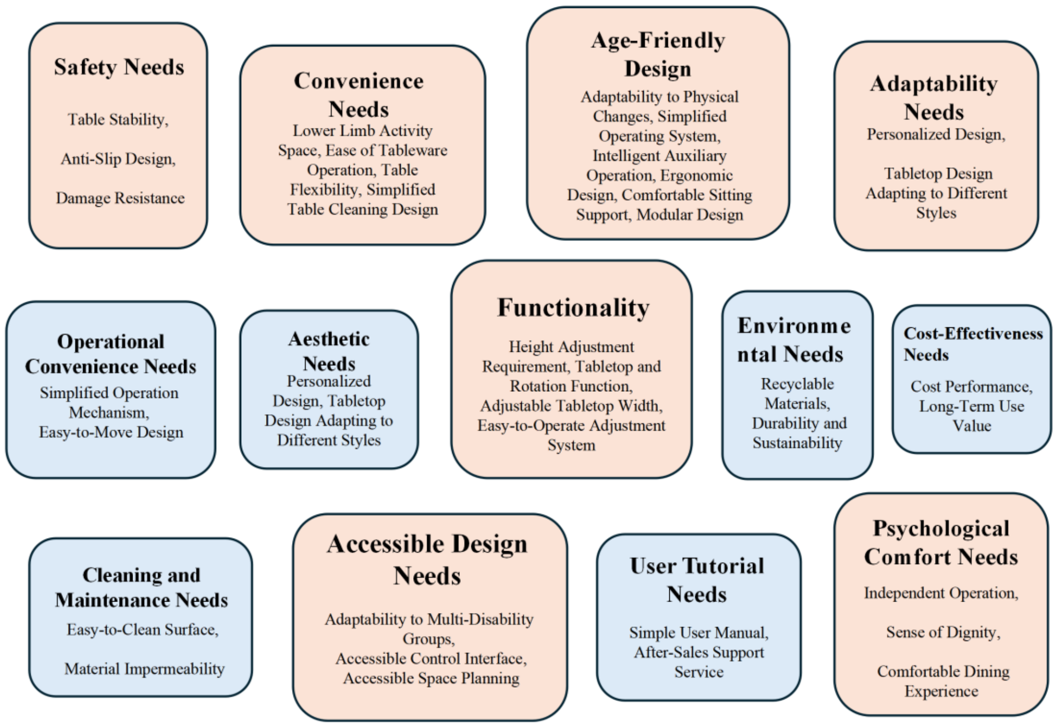

Fig. 4. User indicator needs

Dimensionality Reduction of User Demand Data

Following synthesis and categorization, thirteen user-demand indicators were finalized. A questionnaire survey was administered to 112 participants with no gender quotas using a seven-point Likert scale. In total, 106 valid responses were obtained. The PCA was performed to reduce dimensionality.

Suitability tests indicated that the data were adequate for PCA. As shown in Table 2, the KMO value was 0.879, exceeding the 0.60 threshold for sampling adequacy, and Bartlett's test of sphericity was significant ($\chi^2 = 1190.295$, $df = 78$, $p < 0.001$), supporting factorability.

Table 2. KMO and Bartlett's Test

KMO Measure of Sampling Adequacy		0.879
Bartlett's Test of Sphericity	Approx. Chi-Square	1190.295
	df	78
	Sig.	< 0.001

Component extraction identified four components with eigenvalues greater than one. The percentages of variance explained were 54.355% for Component 1, 12.774% for Component 2, 9.538% for Component 3, and 8.888% for Component 4. The cumulative variance explained was 85.556%, indicating that these four components account for most of the information (Table 3). The scree plot (Fig. 5) shows a clear elbow after the fourth component, confirming the retention of four components.

Table 3. Total Variance Explained

Com-ponent	Initial Eigenvalues			Sum of Squared Loadings Extracted			Sum of Squared Loadings Rotated		
	Total	Percen-tage of Variance	Cumu-lative %	Total	Percen-tage of Variance	Cumu-lative %	Total	Percen-tage of Variance	Cumu-lative %
1	7.066	54.355	54.355	7.066	54.355	54.355	3.986	30.665	30.665
2	1.661	12.774	67.130	1.661	12.774	67.130	3.406	26.198	56.863
3	1.240	9.538	76.667	1.240	9.538	76.667	1.887	14.513	71.376
4	1.155	8.888	85.556	1.155	8.888	85.556	1.843	14.180	85.556
5	0.374	2.879	88.435						
6	0.273	2.102	90.537						
7	0.261	2.009	92.546						
8	0.221	1.698	94.244						
9	0.201	1.547	95.791						
10	0.162	1.248	97.039						
11	0.153	1.181	98.220						
12	0.120	0.926	99.146						
13	0.111	0.854	100.000						

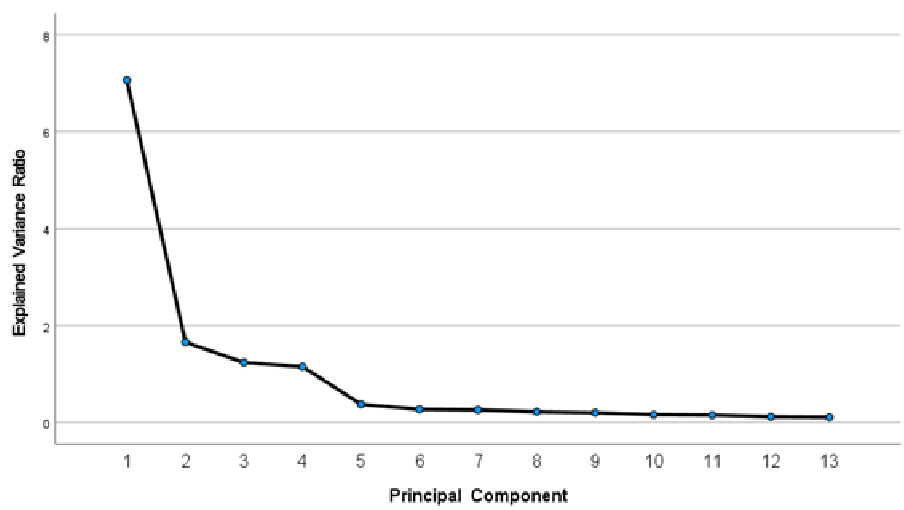

Fig. 5. Gravel map

Because unrotated PCA loadings are difficult to interpret at the variable level, the factor-loading matrix was rotated using varimax with Kaiser normalization. After six iterations, the rotated loadings were well differentiated across four components, yielding a clear simple structure (Table 4). Based on the dominant loadings, Component 1 (User Tutorial, Functional, Operational Convenience, Aesthetic, Psychological Comfort) was labeled Comprehensive Functionality; Component 2 (Cost Effectiveness, Safety, Environmental, Cleaning, and Maintenance) was labeled Value and Safety; Component 3 (Accessible Design, Age-Friendly Design) was labeled Accessible Inclusiveness; and Component 4 (Adaptability, Convenience) was labeled Operational Adaptability. The PCA therefore reduced the original thirteen needs to four interpretable components that underpin the evaluation-indicator system and subsequent weighting.

Table 4. Rotated Component Matrix

Indicator Name	Component			
	1	2	3	4
User Tutorial Needs	0.890	0.182	0.126	0.085
Functional Needs	0.876	0.212	0.146	0.165
Operational Convenience Needs	0.822	0.264	0.264	0.149
Aesthetic Needs	0.818	0.280	0.204	0.102
Psychological Comfort Needs	0.792	0.305	0.166	0.318
Cost-Effectiveness Needs	0.292	0.867	0.084	0.064
Safety Needs	0.219	0.866	0.167	0.214
Environmental Needs	0.253	0.855	0.132	0.154
Cleaning and Maintenance Needs	0.230	0.841	0.148	0.216
Accessible Design Needs	0.228	0.141	0.919	0.079
Age-Friendly Design	0.277	0.209	0.874	0.176
Adaptability Needs	0.162	0.229	0.137	0.874
Convenience Needs	0.222	0.176	0.096	0.868

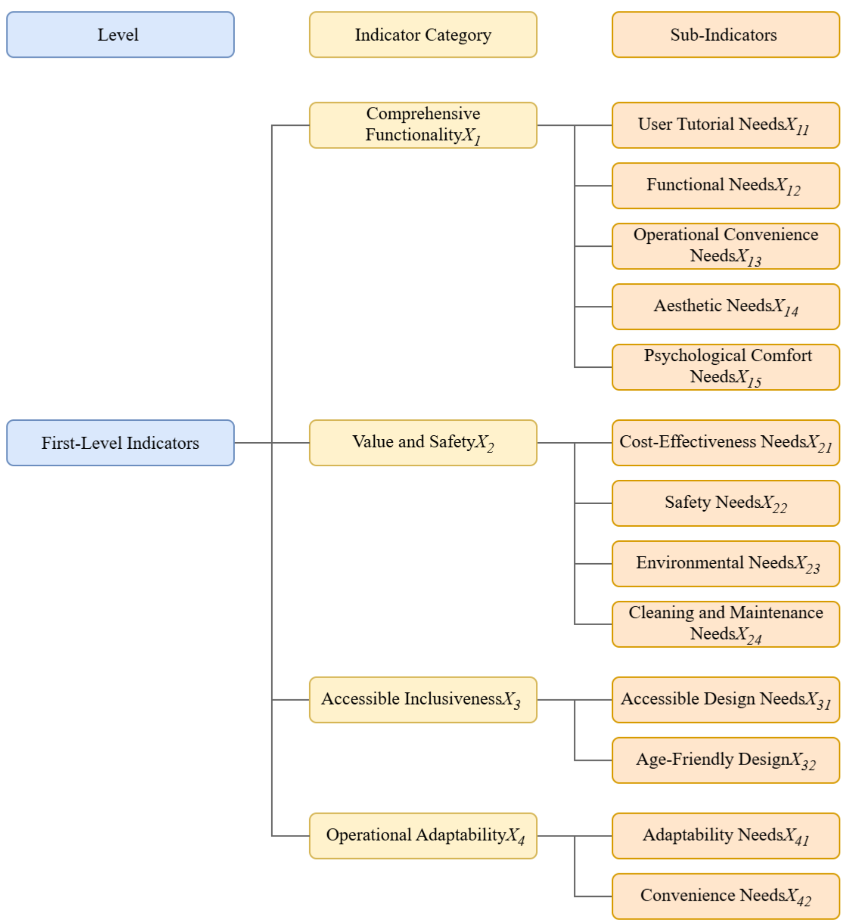

Fig. 6. Evaluation system for multifunctional dining table design

Construction of the Evaluation Indicator System and Calculation of Weights

The four principal-component demand factors from PCA were used to construct a hierarchical evaluation-indicator system (Fig. 6). The criterion layer comprises four first-level indicators: Comprehensive Functionality (X_1), Value and Safety (X_2), Accessible Inclusiveness (X_3), and Operational Adaptability (X_4). Comprehensive Functionality (X_1) includes User Tutorial Needs (X_{11}), Functional Needs (X_{12}), Operational Convenience Needs (X_{13}), Aesthetic Needs (X_{14}), and Psychological Comfort Needs (X_{15}). Value and Safety (X_2) includes Cost-Effectiveness Needs (X_{21}), Safety Needs (X_{22}), Environmental Needs (X_{23}), and Cleaning and Maintenance Needs (X_{24}). Accessible Inclusiveness (X_3) includes Accessible Design Needs (X_{31}) and Age-Friendly Design (X_{32}). Operational Adaptability (X_4) includes Adaptability Needs (X_{41}) and Convenience Needs (X_{42}). Eight experts evaluated the second-level indicators and established an overall order: $X_{12} > X_{31} > X_{13} > X_{32} > X_{42} > X_{41} > X_{22} > X_{14} > X_{15} > X_{21} > X_{11} > X_{23} > X_{24}$. Adjacent-importance ratios were then assigned according to the reference scale in Table 5. Based on these ratios, subjective weights were computed using ORA. As shown in Table 6, Functional Needs had the highest subjective weight, while Cleaning and Maintenance Needs had the lowest.

Table 5. Importance Between Adjacent Indicators

Adjacent Indicator Pair	Judgment Value r_k	Explanation
X_{23}VS.X_{24} (r_{13})	1.6	X_{23} is strongly more important than X_{24}
X_{11}VS.X_{23} (r_{12})	1.4	X_{11} is significantly more important than X_{23}
X_{21}VS.X_{11} (r_{11})	1.2	X_{21} is slightly more important than X_{11}
X_{15}VS.X_{21} (r_{10})	1.2	X_{15} is slightly more important than X_{21}
X_{14}VS.X_{15} (r_9)	1.4	X_{14} is significantly more important than X_{15}
X_{22}VS.X_{14} (r_8)	1.8	X_{22} is extremely more important than X_{14}
X_{41}VS.X_{22} (r_7)	1.4	X_{41} is significantly more important than X_{22}
X_{42}VS.X_{41} (r_6)	1.4	X_{42} is significantly more important than X_{41}
X_{32}VS.X_{42} (r_5)	1.2	X_{32} is slightly more important than X_{42}
X_{13}VS.X_{32} (r_4)	1.2	X_{13} is slightly more important than X_{32}
X_{31}VS.X_{13} (r_3)	1.4	X_{31} is significantly more important than X_{13}
X_{12}VS.X_{31} (r_2)	1.2	X_{12} is slightly more important than X_{31}

Table 6. Calculation Results of ORA Subjective Weights

First-Level Indicator	Weight of First-Level Indicator	Second-Level Indicator	Weight of Second-Level Indicator
X_1	0.434	X_{11}	0.013
		X_{12}	0.235
		X_{13}	0.140
		X_{14}	0.027
		X_{15}	0.019
X_2	0.080	X_{21}	0.016
		X_{22}	0.049
		X_{23}	0.009
		X_{24}	0.006
X_3	0.313	X_{31}	0.196
		X_{32}	0.117
X_4	0.166	X_{41}	0.069
		X_{42}	0.097

To complement expert judgment with data-driven variability, objective weights were calculated using the CRITIC method. Ten experts scored the indicator system on a seven-point Likert scale (Table 7). The CRITIC results (Table 8) show that aging-friendly design (X_{32}) had the highest objective weight, whereas Psychological Comfort Needs (X_{15}) had the lowest.

Table 7. Expert Scoring Table

Evaluation Indicator	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10
X_{12}	6	7	6	5	7	5	6	6	5	7
X_{42}	6	5	5	4	6	5	5	6	5	4
X_{22}	6	6	5	5	4	5	5	6	4	6
X_{31}	7	6	7	7	6	7	7	6	5	6
X_{32}	4	5	4	5	6	6	4	4	5	6
X_{41}	3	5	3	4	4	3	5	4	5	5
X_{24}	2	3	1	3	2	3	4	4	5	1
X_{14}	4	3	3	4	5	2	1	2	2	3
X_{23}	3	2	1	2	3	5	3	4	6	1
X_{15}	4	5	4	4	5	3	4	5	4	4
X_{21}	3	4	3	3	4	2	2	3	2	3
X_{13}	6	7	6	6	4	5	4	5	5	6
X_{11}	2	3	1	1	2	1	1	2	3	2

After obtaining the expert evaluation data, the objective weight results were calculated using the CRITIC method (Table 8). Through the objective weight analysis of the CRITIC method, it can be seen that the weight of the aging-friendly design indicator (X_{32}) was the highest, while the weight of the Psychological Comfort Needs indicator (X_{15}) was the lowest.

Table 8. Calculation Results of CRITIC Objective Weights

Evaluation Indicator	Variability	Conflict	Information Amount	Weight
X_{12}	0.408	10.089	4.119	0.075
X_{42}	0.369	11.475	4.234	0.077
X_{22}	0.394	11.53	4.548	0.083
X_{31}	0.35	15.031	5.255	0.096
X_{32}	0.438	12.375	5.418	0.099
X_{41}	0.438	11.602	5.079	0.092
X_{24}	0.329	13.17	4.335	0.079
X_{14}	0.299	11.148	3.337	0.061
X_{23}	0.327	13.583	4.436	0.081
X_{15}	0.316	9.55	3.02	0.055
X_{21}	0.369	9.578	3.534	0.064
X_{13}	0.322	11.643	3.749	0.068
X_{11}	0.394	9.785	3.859	0.070

Finally, a subjective–objective integration strategy was applied, assigning equal importance to ORA and CRITIC (50% each) to obtain comprehensive weights (Table 9). The resulting ranking, in descending order, was: Functional Needs (X_{12}) > Accessible Design Needs (X_{31}) > Age-Friendly Design (X_{32}) > Operational Convenience Needs (X_{13}) > Convenience Needs (X_{42}) > Adaptability Needs (X_{41}) > Safety Needs (X_{22}) > Environmental Needs (X_{23}) > Aesthetic Needs (X_{14}) > Cleaning and Maintenance Needs (X_{24}) > User Tutorial Needs (X_{11}) > Cost-Effectiveness Needs (X_{21}) > Psychological Comfort Needs (X_{15}).

Table 9. Comprehensive Weight Ranking Results of the Evaluation Indicator System

First-Level Indicator	Second-Level Indicator	Subjective Weight	Objective Weight	Comprehensive Weight	Comprehensive Weight Ranking
X_1	X_{11}	0.013	0.070	0.042	11
	X_{12}	0.235	0.075	0.155	1
	X_{13}	0.140	0.068	0.104	4
	X_{14}	0.027	0.061	0.044	9
	X_{15}	0.019	0.055	0.037	13
X_2	X_{21}	0.016	0.064	0.040	12
	X_{22}	0.049	0.083	0.066	7
	X_{23}	0.009	0.081	0.045	8
	X_{24}	0.006	0.079	0.043	10
X_3	X_{31}	0.196	0.096	0.146	2
	X_{32}	0.117	0.099	0.108	3
X_4	X_{41}	0.069	0.092	0.081	6
	X_{42}	0.097	0.077	0.087	5

Design Schemes

Guided by the comprehensive weight rankings, three multifunctional dining-table concepts were developed for older adults with disabilities (Fig. 7). Each concept prioritizes the four highest-ranked indicators, Functional Needs, Accessible Design Needs, Operational Convenience Needs, and Age-Friendly Design, to address diverse physical capabilities, usage scenarios, and psychological comfort.

Scheme 1. The design centers on user operations and supports automatic tabletop rotation to facilitate reach to tableware and angle adjustment during meals. An integrated control system with multi-sensor inputs enables powered height adjustment (range: 680–880 mm) calibrated to individual differences. Hygiene is enhanced through a built-in ultraviolet disinfection module, while refrigeration and storage units increase practicality. For accessible use, remote-controlled posture adjustment improves approachability, ensuring a knee clearance height of >650 mm. Edge protection with anti-collision and anti-slip materials and an optional surface warming function further support safety and comfort.

Scheme 2. A foldable tabletop combining semi-circular and square modules expands (max width: 1200 mm) or contracts (folded width: 450 mm) to suit party size and spatial constraints. A modular function unit between the top and the support column augments storage, disinfection, and cleaning capabilities. An intelligent adjustment system automatically sets tabletop height (adjustable between 680 and 880 mm) and angle to user conditions. For older adults with disabilities, a touch-control panel with clear pathways and immediate feedback improves convenience and comfort in daily use.

Scheme 3. The concept employs adaptive adjustment with embedded sensors and control algorithms that infer user status and adjust tabletop parameters in real time. Height (adjustability: 680 to 880 mm) and width (adaptive range: 900 to 1200 mm) adapt to posture, wheelchair position, and tableware access needs to achieve an ergonomically optimized configuration. Voice control enables hands-free adjustments. Sub-table disinfection, storage, and refrigeration modules support personalized storage and post-meal handling, improving comfort, safety, adaptability, and overall intelligence.

Fig. 7. Design schemes

Determination of the Optimal Scheme

To compare and select among the three concepts, twenty participants were recruited, including five accessible-design experts, five furniture-design experts, and ten target users. To ensure methodological rigor and data credibility, a stratified sampling strategy with strict inclusion criteria was implemented. The expert panel (n=10) was divided based on domain expertise: the five accessible-design experts were selected for their mastery of ergonomic standards and universal design principles (requiring a minimum of five years in research or practice), while the five furniture-design experts were recruited based on their practical experience in structural engineering and mass-production processes. Concurrently, the ten target users were screened to guarantee the ecological validity of the feedback. The inclusion criteria for users were: (1) verified status as long-term wheelchair users or older adults with functional limitations; (2) sufficient cognitive capacity to comprehend the evaluation metrics independently; and (3) a minimum of one year of daily experience with accessible dining scenarios to ensure familiarity with usage pain points. Each concept was evaluated against the second-level indicators in the multifunctional dining-table evaluation system, and mean scores were computed to form the initial decision matrix (Table 10). TOPSIS was then applied using the comprehensive indicator weights derived earlier (Table 9), treating all indicators as benefit-type. The positive-ideal, negative-ideal, and relative closeness values were calculated, and the concepts were ranked accordingly (Table 11). The result was Scheme 2 > Scheme 1 > Scheme 3, with Scheme 2 selected as the top-performing design.

Table 10. Initial Decision Matrix

Second-Level User Indicator	Design Scheme 1	Design Scheme 2	Design Scheme 3
User Tutorial Needs X_{11}	6.9	7.0	7.1
Functional Needs X_{12}	7.7	8.2	7.6
Operational Convenience Needs X_{13}	7.8	8.1	8.0
Aesthetic Needs X_{14}	6.8	6.9	7.0
Psychological Comfort NeedsX_{15}	6.7	6.7	6.9
Cost-Effectiveness Needs X_{21}	7.4	6.8	7.2
Safety Needs X_{22}	7.2	7.1	6.9
Environmental Needs X_{23}	7.1	6.9	7.0
Cleaning and Maintenance Needs X_{24}	7.2	7.3	7.1
Accessible Design Needs X_{31}	7.9	8.1	8.0
Age-Friendly DesignX_{32}	8.0	8.1	7.9
Adaptability NeedsX_{41}	7.9	8.2	7.8
Convenience NeedsX_{42}	7.5	7.7	7.4

Table 11. Calculation Results of TOPSIS

Design Scheme	Distance to Positive Ideal Solution D_i^+	Distance to Negative Ideal Solution D_i^-	Relative Proximity C_i	Ranking Result
Design Scheme1	0.267	0.164	0.381	2
Design Scheme2	0.139	0.319	0.696	1
Design Scheme3	0.306	0.132	0.302	3

Ergonomic Verification

In the ergonomic simulation, digital human models and virtual environments were constructed (Fig. 8). Task scripts were assigned to the models to reproduce real-world dining behaviors. Kinematic, reach, visibility, and spinal-load metrics were obtained using digital human-modeling software and used to refine the design.

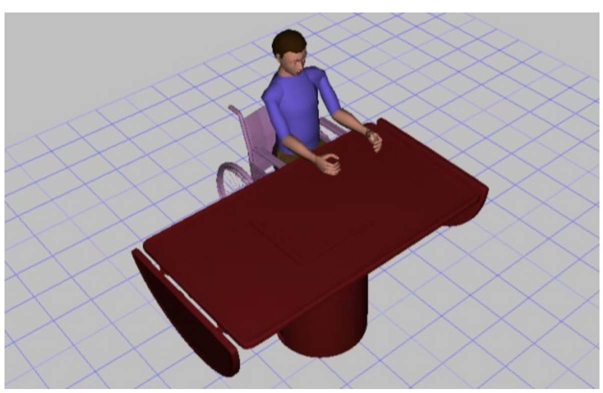

Fig. 8. Virtual scenario

The reach envelope (Fig. 9) links human capability to product geometry and enables digital optimization of the multifunctional dining table. From the limb reach results, older users' dining postures remained within natural reach or maximal functional reach. All required operations were achievable without excessive limb stretching or trunk twisting, reducing the risk of muscle strain.

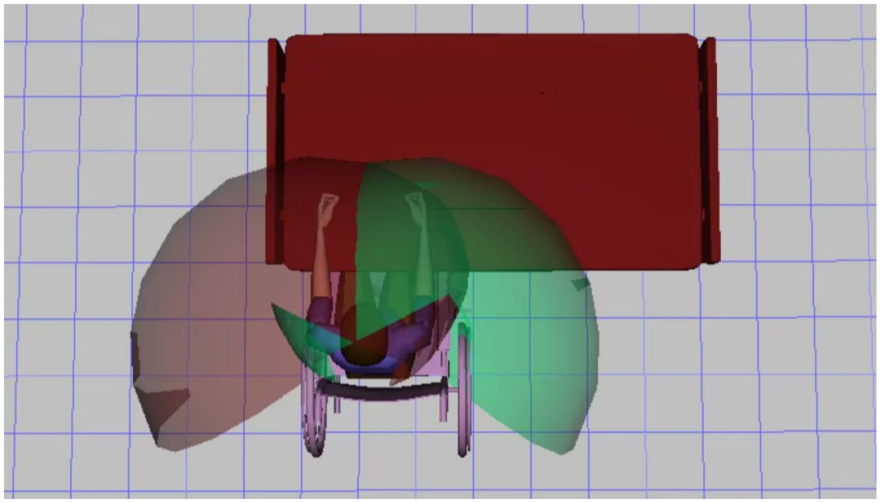

Fig. 9. Ergonomic simulation reachable area

Figure 10 illustrates the binocular visual field for the current posture. The transparent hemisphere denotes overall visual space, and the transparent visual cone shows the direction of gaze. The key focus areas fall within the comfortable field of view with no salient blind spots, indicating that older users can obtain necessary visual information without obstruction.

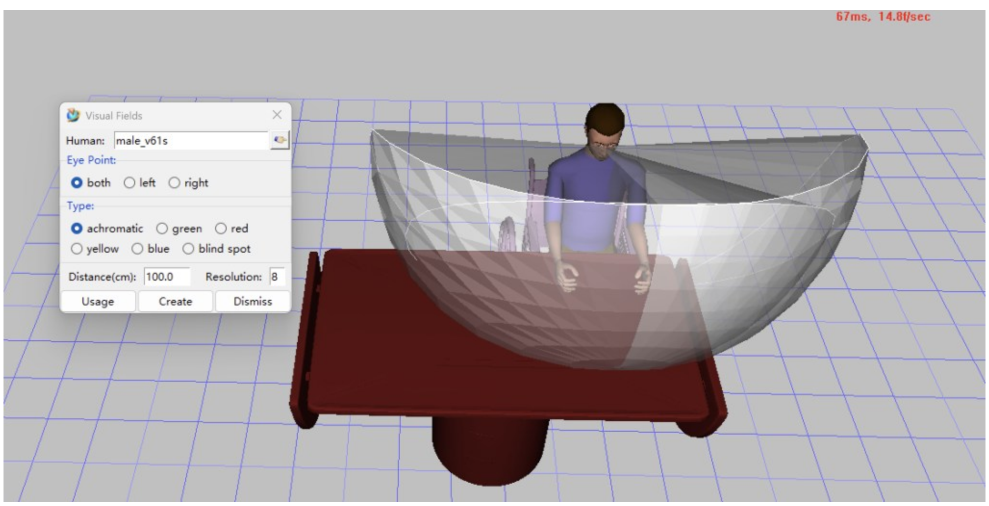

Fig. 10. Visual field range

Lumbar loading was evaluated with the software's lower-back analysis tool. Following the manual developed by the National Institute for Occupational Safety and Health (NIOSH), the recommended maximum allowable compressive load in this region is 3400 N (Ashley 2015). The simulated L4/L5 compressive load was 486 N (Fig. 11), which is below the recommended limit, supporting safe use for older adults with disabilities.

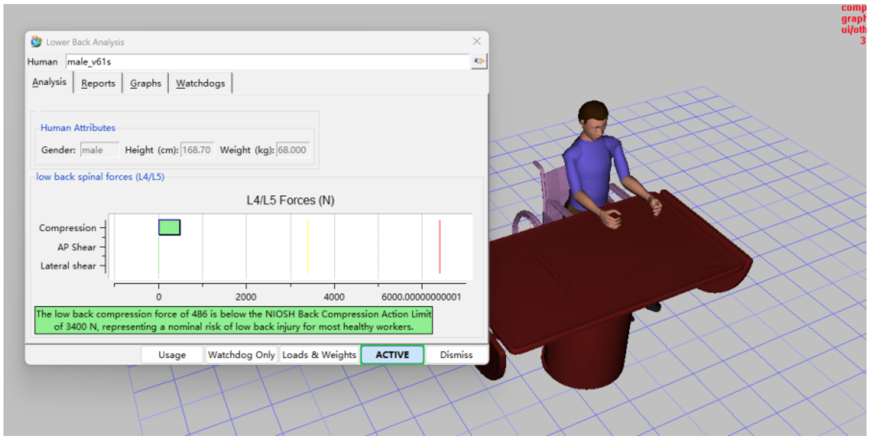

Fig. 11. Dynamic analysis of lumbar spine stress

Seated comfort was assessed using the Comfort Assessment tool on a 0 to 80 scale, where higher scores indicate poorer comfort. The results were: neck 12.5, shoulder 25.2, hip 47.2, back 0, right arm 0, left arm 0, right leg 8.8, left leg 8.7, fatigue 38.4, and overall 44.2 (Fig. 12). All part scores were below 60, indicating acceptable comfort consistent with ergonomic requirements. The simulation therefore verified the ergonomic soundness of the optimal concept and supports a user-centered design rationale.

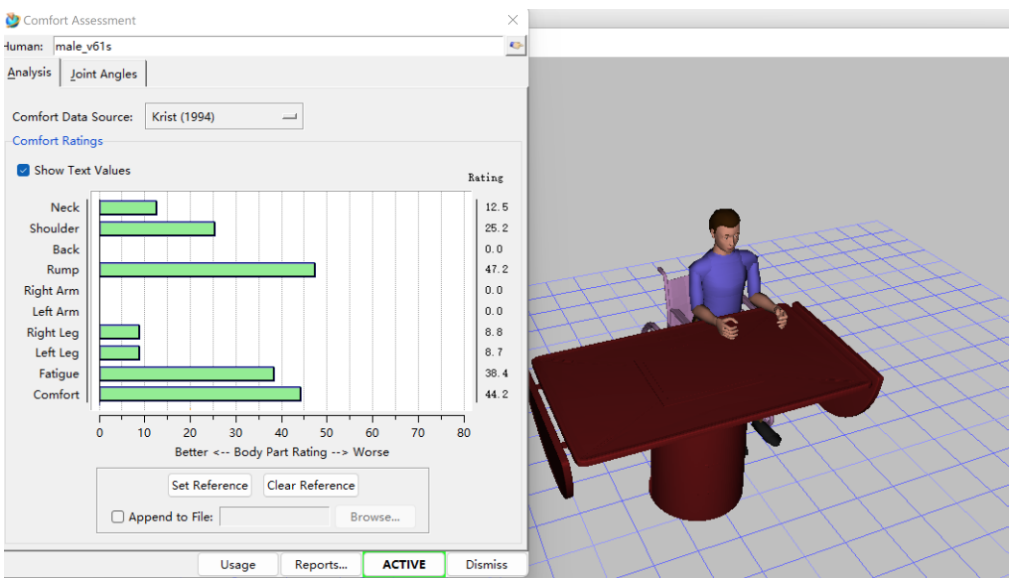

Fig. 12. Human comfort evaluation

CONCLUSIONS

1. Drawing on user-journey mapping and principal component analysis (PCA), this study identified four factors shaping the accessible dining experience: Comprehensive Functionality, Value and Safety, Accessible Inclusiveness, and Operational Adaptability. Integrating order relation analysis (ORA) and criteria importance through intercriteria correlation (CRITIC) weighting showed that Functional Needs, Accessible Design Needs, Operational Convenience, and Age-

Friendly Design were the most influential indicators, providing a quantitative basis for design decisions.

2. Guided by the comprehensive weights, three multifunctional dining-table Schemes were evaluated with TOPSIS. The closeness coefficients were Ci = 0.696 for Scheme 2, Ci = 0.381 for Scheme 1, and Ci = 0.302 for Scheme 3, ranking Scheme 2 first. Anchored by a modular foldable structure with intelligent height adjustment and a touch-control interface, Scheme 2 delivered the strongest performance in functionality, safety, and adaptability.
3. Ergonomic simulation indicated an L4/L5 compressive load of 486 N, below the NIOSH recommended limit of 3400 N, and an overall comfort score of 44.2 on a 0 to 80 scale. Visual analysis showed key targets within a 0 to 100 cm viewing range, consistent with ergonomic requirements. Together, these results support the ergonomic and practical feasibility of the proposed design and its potential to enhance the accessible dining experience for older adults with disabilities.

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To ensure research integrity and transparency, the authors declare that ChatGPT (OpenAI) was used exclusively for English translation and language refinement. All aspects of research design, data analysis, and the formulation of conclusions were independently conducted by the authors.

REFERENCES CITED

Ashley, K. (2015). “NIOSH manual of analytical methods 5th edition and harmonization of occupational exposure monitoring,” *Gefahrstoffe Reinhaltung der Luft* 75(1–2), 7-16.

Chang, J., Han, H., and Yuan, K. (2025). “How can regional cultural symbols be integrated into public seating design? An innovative exploration using marbled porcelain patterns as an example,” *BioResources* 20(4), 8420-8438. https://doi.org/10.15376/biores.20.4.8420-8438

Cho, H., MacLachlan, M., Clarke, M., and Mannan, H. (2016). “Accessible home environments for people with functional limitations: A systematic review,” *International Journal of Environmental Research and Public Health* 13(8), article 826. https://doi.org/10.3390/ijerph13080826

Fu, L., Yang, X., Zhu, L., and Lv, J. (2025). "An intelligent optimization design method for furniture form considering multi-dimensional user affective requirements," *Symmetry* 17(9), article 1406. https://doi.org/10.3390/sym17091406

Gupta, A., Yadav, M., and Nayak, B. (2025). "A systematic literature review on inclusive public open spaces: Accessibility standards and universal design principles," *Urban Science* 9(6), article 181. https://doi.org/10.3390/urbansci9060181

Lin, M., Wang, C., Chen, M., and Chang, C. (2008). "Using AHP and TOPSIS approaches in customer-driven product design process," *Computers in Industry* 59(1), 17-31. https://doi.org/10.1016/j.compind.2007.05.013

Lindgaard, G., Dillon, R., Trbovich, P., White, R., Fernandes, G., Lundahl, S., and Pinnamaneni, A. (2006). "User needs analysis and requirements engineering: Theory and practice," *Interacting with Computers* 18(1), 47-70. https://doi.org/10.1016/j.intcom.2005.06.003

Lisle, A., Merenda, C., and Gabbard, J. (2020). "Using affinity diagramming to generate a codebook: A case study on young military veterans and community reintegration," *Qualitative Research* 20(4), 396-413. https://doi.org/10.1177/1468794119851324

Lui, L., and Lee, C. (2023). "Modelling of earphone design using principal component analysis," *Applied Sciences* 13(17), article 9912. https://doi.org/10.3390/app13179912

Nageb Fewella, L. (2024). "The behavioral smart furniture and its relevance to family emotional dynamics," *Ain Shams Engineering Journal* 15(11), article 103030. https://doi.org/10.1016/j.asej.2024.103030

Patil, A., and Raghani, S. (2025). "Designing accessible and independent living spaces for visually impaired individuals: A barrier-free approach to interior design," *International Journal for Equity in Health* 24(1), article 137. https://doi.org/10.1186/s12939-025-02503-5

Patrick, V., and Hollenbeck, C. (2021). "Designing for all: Consumer response to inclusive design," *Journal of Consumer Psychology* 31(2), 360-381. https://doi.org/10.1002/jcpy.1225

Ren, Z., and Qu, M. (2024). "A hybrid FKANO-CRITIC-CCD model for furniture design and evaluation," *Journal of Intelligent & Fuzzy Systems* 46(1), 2789-2810. https://doi.org/10.3233/JIFS-235272

Wang, L., Gong, Y., Niu, S., and Ren, Z. (2025). "Cultural symbols migration and user perception: Innovation in Chinese-style furniture design," *BioResources* 20(2), 3476-3496. https://doi.org/10.15376/biores.20.2.3476-3496

Widjaja, W., and Takahashi, M. (2016). "Distributed interface for group affinity-diagram brainstorming," *Concurrent Engineering: Research and Applications* 24(4), 344-358. https://doi.org/10.1177/1063293X16657860

Yu, C., Liu, W., Fei, Y., Chen, J., and Hu, Z. (2025). "Research on the design elements of air pressure massage cushion for expanding the elderly-friendly functions of furniture," *BioResources* 20(3), 5988-6018. https://doi.org/10.15376/biores.20.3.5988-6018

Yu, S., Liu, M., Chen, L., Chen, Y., and Yao, L. (2024). "Emotional design and evaluation of children's furniture based on AHP-TOPSIS," *BioResources* 19(4), 7418–7433. https://doi.org/10.15376/biores.19.4.7418-7433

Zhang, H., Zeng, L., and Song, J. (2025). "Applying the deep learning model into the furniture product design for the elderly," *Journal of Mechanics in Medicine and Biology* 25(5), article 305. https://doi.org/10.1142/S0219519425400305

Zhang, Z., Zhan, Z., and Li, Y. (2025). "User-designer cognitive synergy: Enhancing Age-Friendly rural public space design," *Buildings* 15(17), article 3078. https://doi.org/10.3390/buildings15173078

Zhou, C., Huang, T., Luo, X., Kaner, J., and Fu, X. (2022). "Recognition and analysis of an Age-Friendly intelligent sofa design based on skeletal key-points," *International Journal of Environmental Research and Public Health* 19(18), article 11522. https://doi.org/10.3390/ijerph191811522

Zhou, C., Yu, R., and Kaner, J. (2024). "Evaluating functional ability in older adults' object retrieval behavior from kitchen furniture using OpenPose and REBA," *Scientific Reports* 14(1), article 25560. https://doi.org/10.1038/s41598-024-75470-6

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