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Research on design strategies of AR intelligent kitchen experience based on user profiling

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Abstract. To enhance the precision and adaptability of user experience in home intelligent kitchen scenarios and to promote the appropriate application of Augmented Reality (AR) technology in domestic cooking contexts, this study adopts a lifestyle segmentation perspective. Focusing on the behavioral characteristics and experiential needs of users in home intelligent kitchens, quantitative methods—including questionnaire surveys, factor analysis, and cluster analysis—are employed to systematically classify and identify the characteristics of home cooking user groups. The results indicate significant differences among user groups in their usage scenarios within intelligent kitchens. Based on these differences in user characteristics, the study proposes three corresponding design strategies: optimization of interface information visualization, design strategies for users with low vision, and a narrative experience–oriented design approach. These strategies aim to establish a more targeted and differentiated AR experience design framework for home-based fresh cooking environments.

Keywords: experience design, interaction design, design strategy, smart kitchen, augmented reality

1. Introduction

An intelligent kitchen is a kitchen system that integrates advanced technologies such as the Internet of Things (IoT) and artificial intelligence. By installing various smart devices and sensors, it enables real-time monitoring and intelligent control of the kitchen environment. Meanwhile, benefiting from China's rapid economic growth and technological progress, the smart home market has expanded significantly, and Augmented Reality (AR) technology has gradually become an important development direction in the field of smart homes. In light of the current trend toward whole-house intelligent systems and breakthroughs in AR hardware performance, the application of AR technology in home intelligent kitchen scenarios has the potential to optimize the process of purchasing fresh ingredients and enhance the overall home cooking experience. The integration of AR technology with intelligent kitchens—particularly through hardware devices such as AR glasses that provide guidance on healthy eating and interconnect with smart refrigerators—represents an important direction for the future development of intelligent kitchens.

2. Relevant theoretical foundations and research background

2.1. Research on home intelligent kitchens

According to Mills et al. [1], whose study examines the health and social determinants of home cooking, the scenario of a home intelligent kitchen refers to the set of activities carried out within the specific physical environment of a domestic kitchen to prepare cold or hot food. These activities include combining ingredients, mixing them, and typically applying heat during the cooking process. The determinants influencing home cooking operate across multiple levels, including the individual, household, community, and cultural contexts. Key influencing factors include the user's gender, available discretionary time and employment status, close interpersonal relationships, and cultural or ethnic background. Another key characteristic of intelligent kitchen scenarios is the emphasis on the timeliness, freshness, and high nutritional value of ingredients. As consumers pay increasing attention to healthy diets, the demand for convenient and health-oriented lifestyles continues to grow. In this context, AR technology can provide users with real-time cooking guidance, including information on ingredient proportions, animated demonstrations of cooking procedures, timing reminders, and suggestions for heat control. Such functions can significantly improve both the efficiency and the overall experience of cooking. While China's smart home market is undergoing rapid expansion, it also faces a series of challenges, which require coordinated efforts across industries to achieve sustainable development [2].

2.2. Research on user needs analysis

In product and service design research, user needs analysis constitutes an essential foundation for developing design strategies and optimizing user experience pathways. Compared with traditional approaches that classify users solely based on demographic variables, recent studies emphasize a more systematic segmentation of user groups based on deeper dimensions, including behavioral patterns, value orientations, and lifestyle structures [3]. The AIO scale—measuring Activities, Interests, and Opinions—has long been regarded as a classic tool for assessing lifestyle characteristics and is widely applied in user segmentation and the analysis of user need structures. The AIO measurement framework evaluates three primary dimensions: activities, interests, and opinions, encompassing both users' internal psychological states and their external behavioral patterns. As early as 1971, Well and Tiger developed a 300-item AIO inventory designed to measure a wide range of psychological variables such as consumer personality traits, attitudes, values, interests, and purchasing motivations, thereby providing a comprehensive understanding of consumer profiles. Subsequent revisions simplified the instrument into a structure consisting of three principal dimensions and thirty-six subdimensions. In recent years, researchers investigating lifestyle segmentation have frequently employed AIO-based survey instruments to explore segmented lifestyle markets and corresponding user groups.

2.3. Research on user personas

In interaction design and user experience research, user personas are widely recognized as an important user-centered design tool. The widespread adoption of this concept is largely attributed to the About Face series authored by Alan Cooper. Cooper emphasizes that personas are virtual archetypes constructed on the basis of qualitative research data about target user groups. Their purpose is to assist designers in better understanding and empathizing with users' needs, goals, and behavioral patterns throughout the product development process. These personas typically include detailed information about users' backgrounds, skill levels, attitudes, motivations, pain points, and the contexts in which they interact with products or systems [4].

Before constructing user personas, it is necessary to clarify the objectives of the research. In this study, the interview theme was defined as "an investigation of consumer habits and behavioral preferences among users purchasing fresh ingredients for home cooking". Based on this objective, an interview outline was developed, and observational records were conducted within home cooking scenarios. Drawing on the five-element model of interaction design proposed by Professor Xiangyang Xin in Interaction Design: From Physical Logic to Behavioral Logic, statistical analysis of users' home fresh-cooking behaviors was conducted through both questionnaire surveys and user interviews [5].

3. Construction process of user personas for the home intelligent kitchen

The construction of user personas is a comprehensive process aimed at achieving an in-depth understanding of target user groups and providing a basis for optimizing product experience. For the home fresh-cooking user group, the development of user personas generally follows four core steps: data collection and preprocessing, extraction of characteristic factors, persona identification and cluster analysis, and visual presentation.

3.1. Conceptual approach to user persona construction

The central objective of constructing user personas for the home intelligent kitchen is to optimize the user experience of fresh-ingredient purchasing platforms through a deeper understanding of users, thereby improving user satisfaction and enabling more precise recommendations for dietary combinations. The AIO lifestyle scale is employed to integrate information on users' purchasing and cooking behaviors, dietary preferences, and interest orientations. User personas are developed through a combination of quantitative questionnaire research and qualitative research methods to collect data on user feedback and purchasing preferences. From these data, the core characteristic factors representing home fresh-cooking users are extracted and subsequently subjected to cluster analysis. Finally, the resulting personas are presented in an intuitive and easily interpretable form through visualized word clouds (see Fig. 1).

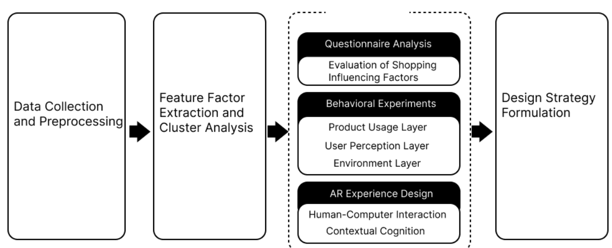


Figure 1. Design thinking for user persona qualitative research (author's own illustration)

3.2. Qualitative research design for user personas

The qualitative research design of user personas constitutes a critical stage for gaining deeper insight into the behaviors, motivations, and emotional responses of target users. Based on four aspects of the AIO lifestyle scale—"user activities", "interests", "opinions", and "user habits"—this study focuses on the "active and health-oriented" user group. Within this framework, key home kitchen scenarios are examined, including the smoothness of kitchen interaction, social sharing, and cooking guidance. Taking the case of a user wearing a PICO4 Ultra device, a user journey map was developed to illustrate the process of the home AR cooking experience (see Fig. 2).

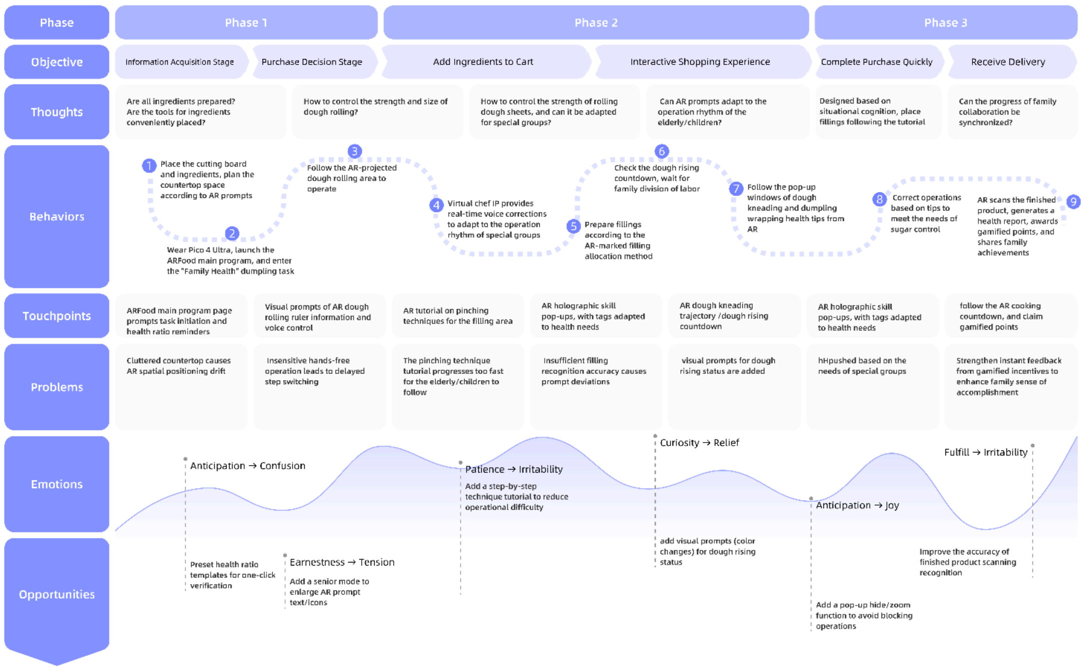


Figure 2. User journey map of AR home cooking experience (author's own illustration)

3.3. Design of user persona label weights

Table 1. Total variance explained (author's own illustration)

Total Variance Explained							
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	7.018	16.322	16.322	7.018	16.322	16.322	6.728
2	5.944	13.824	30.146	5.944	13.824	30.146	6.265
3	2.086	4.85	34.996	2.086	4.85	34.996	1.884
4	1.67	3.883	38.88	1.67	3.883	38.88	1.525
5	1.596	3.711	42.59	1.596	3.711	42.59	1.661
6	1.446	3.363	45.953	1.446	3.363	45.953	1.689
…	…	…	…				
41	0.197	0.459	99.333				
42	0.146	0.341	99.674				
43	0.14	0.326	100				

Based on questionnaire survey data, subsequent procedures include data processing, persona identification, cluster analysis, and visualization of the results. A total of 43 lifestyle component variables were statistically extracted and subjected to total variance analysis (see Table 1), followed by rotated component factor analysis (see Table 2). Among the variables, home user activities included five survey variables, user interests included four variables, home user opinions included six variables, and user habits included three variables. After identifying user characteristic factors through the factor analysis module in SPSS, the resulting factors were categorized into several groups: visual experience factors, ingredient 3D presentation factors, intelligent shopping recommendation factors, multimodal interaction factors, and AR cost perception factors (see Tables 3 and 4). The core characteristic terms of each user group are then visualized, typically in the form of a word cloud. In this representation, labels with higher weights appear with larger font sizes or deeper colors, indicating their greater significance within the corresponding user persona profile.

Table 2. Rotated component matrix (author's own illustration)

	Component					
	1	2	3	4	5	6
A Interaction fluency	0.743					
A Social sharing	0.781					
A Proactive recommendation	0.745					
I Personalized recommendation	0.744					
O Information accuracy	0.768					
O Privacy protection	0.735					
A AR-glasses guidance		0.834				
I Active interaction		0.736				
I Shopping guidance		0.834				
O Product display		0.879				
D Frequency of use		0.746				
A Convenient operation			0.780			
I Promotional activities			0.838			
O Intelligent recommendation			0.619			
A Ingredient display				0.961		
D Reward mechanisms				0.901		
O Privacy protection					0.738	
O Visual feedback					0.768	
D Identity needs						0.724

Table 3. Clustering scheme and discriminant indicators of user personas for the home fresh-cooking group (author's own illustration)

Characteristic Factor	Cluster = 3		Cluster = 4		Cluster = 5		Cluster = 6	
	F	Sig	F	Sig	F	Sig	F	Sig
Visual experience factor	415.873	.000	392.114	.000	368.902	.000	351.667	.000
Ingredient 3D presentation factor	501.781	.000	476.235	.000	442.690	.000	421.308	.000
Intelligent shopping recommendation factor	338.792	.000	321.406	.000	305.118	.000	289.774	.000
Multimodal interaction factor	466.319	.000	439.227	.000	412.553	.000	398.146	.000
Usage tendency factor	2.353	.126	1.984	.142	1.706	.169	1.522	.203
AR cost perception factor	1.373	.242	1.215	.297	1.048	.331	0.936	.388

Table 4. Mean and central values of characteristic factors when clustered into three categories (author's own illustration)

Characteristic Factor	Cluster 1	Cluster 2	Cluster 3
Visual experience factor	0.715	-0.191	-0.747
Ingredient 3D presentation factor	0.196	-0.113	0.028
Intelligent shopping recommendation factor	0.068	-0.205	0.340
Multimodal interaction factor	-0.928	0.187	-0.259
Usage tendency factor	-1.050	0.731	-0.226
AR cost perception factor	0.112	0.091	0.356

After completing the cluster analysis and determining the three-cluster solution, the mean values of each cluster across the characteristic factors were further calculated in order to characterize differences among user groups. Based on the distribution of mean values across these factors, clear distinctions can be identified among different user groups in terms of visual experience, functional preferences, multimodal interaction styles, and cost perception, thereby providing a basis for the naming and interpretation of user types.

The first user group (Cluster 1) shows a significantly higher positive score on the visual experience factor (0.715). At the same time, positive scores are also observed for ingredient 3D presentation and intelligent shopping recommendation dimensions, indicating that this group demonstrates a relatively strong acceptance of immersive visual presentation and technology-enhanced experiences. However, the scores for multimodal interaction (−0.928) and usage tendency (−1.050) are notably low, suggesting that these users prefer passively experiencing visual content and exhibit comparatively weaker willingness to engage in complex interactive operations or sustained system use. Overall, this group may be characterized as "visual experience–oriented users", whose primary concerns center on intuitive perception and display effects.

The second user group (Cluster 2) exhibits a strong positive characteristic on the usage tendency factor (0.731) and also shows a moderately positive score in multimodal interaction (0.187), indicating a relatively high level of practical system use and interactive participation. In contrast, the scores for visual experience (−0.191), 3D presentation (−0.113), and intelligent recommendation (−0.205) are relatively low. This suggests that these users focus more on functional practicality rather than immersive experience or technological novelty. Therefore, this group can be defined as "function and usage-oriented users", whose behavioral characteristics emphasize operability and sustained practical value.

The third user group (Cluster 3) demonstrates relatively high positive scores in intelligent shopping recommendation (0.340) and AR cost perception (0.356), indicating a strong sensitivity to intelligent decision-support functions and cost efficiency. However, relatively low scores are observed for visual experience (−0.747), multimodal interaction (−0.259), and usage tendency (−0.226), suggesting that these users place limited emphasis on immersive experiences and interactive design, and instead tend to evaluate technologies more rationally based on their functional benefits. This group can therefore be summarized as "rational evaluation and cost-sensitive users".

Overall, the three-cluster solution exhibits clear and significant differences across the core experiential dimensions. It avoids the information loss that might result from excessive simplification while also preventing the structural complexity and reduced interpretability associated with solutions involving a larger number of clusters. Consequently, the three-cluster model achieves an effective balance between statistical discriminability and theoretical interpretability, providing a solid foundation for subsequent user persona construction and strategy analysis.

4. Empirical analysis

4.1. Questionnaire design and data collection

Based on the AIO scale framework, market segmentation was divided into four dimensions: A – Activity (User Activities); I – Interest (User Interests); O – Opinion (User Opinions); D – Demand (User Demand Characteristics). Keywords were classified into primary and secondary categories and summarized as shown in Table 5. Based on this categorization, a complete 26-item questionnaire was designed. A total of 400 respondents participated in the formal survey. After removing invalid responses, 340 valid questionnaires were obtained. The data were entered into SPSS statistical software, and after handling missing values and reverse-coded items, frequency analysis was conducted for the 26 questions listed in Appendix 1 (see Table 5).

Table 5. Summary of functional characteristics of home cooking

Primary Category	Secondary Category	Description
A User Activities	A1 Functional Features	Whether the user uses online fresh food shopping functions
	A2 Voice Interaction	Whether the user prefers voice over typing for interaction
	A3 Gesture Interaction	Willingness to use gesture-based interaction
	A4 User Experience	Factors affecting user experience
I User Interests	I1 Knowledge Level	User's familiarity with shopping scenarios
	I2 Usage Habit	Frequency and regularity of online shopping
	I3 User Preference	Shopping type and dietary preference proportion
	I4 User Rewards	Incentives and rewards gained from shopping
O User Opinions	O1 Product Features	Features and reasons for using the product
	O2 User Decisions	Influence of product visual effects on decisions
	O3 Purchase Intention	Degree to which recipe recommendations influence combined purchases
D User Characteristics	D1 Gender	User gender
	D2 Age	User age
	D3 Occupation	User occupation

4.2. Sample characteristics and reliability & validity test

Prior to factor analysis, the reliability and validity of the scale were examined. The overall Cronbach's α coefficient for the 43-item scale used in this study was 0.763. According to established criteria, a Cronbach's α greater than 0.7 indicates good internal consistency, suggesting that the scale demonstrates stable and reliable measurement performance suitable for subsequent statistical analyses.

For the construction of user personas, the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity (see Tables 6 and 7) were conducted to assess the suitability of the data for factor analysis. The results indicate that the data meet requirements for both internal consistency and structural adequacy, providing a statistical foundation for extracting user persona dimensions and identifying characteristic factors.

Table 6. Reliability and validity test

Reliability Statistics	
Cronbach's Alpha	Number of Items
0.763	43

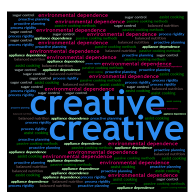
Table 7. KMO and Bartlett test

KMO Sampling Adequacy		0.815
Bartlett's Test of Sphericity	Approx. Chi-Square	6,383.392
	Degrees of Freedom	903
	Significance	0

To further validate the appropriateness of the number of extracted factors, a scree plot was created to analyze the eigenvalue trends of each component. The horizontal axis represents the component number, while the vertical axis represents the eigenvalue. Combining the scree plot's inflection point with the Kaiser criterion (eigenvalues > 1) and the total variance explained results, it was determined that extracting the first six common factors adequately reflects the structure of the original variables. The factor extraction results demonstrate good stability and interpretability, providing a reliable basis for subsequent factor rotation and structural interpretation.

4.3. Factor analysis and classification label extraction

Table 8. Population characteristics and word cloud visualization of home user personas

User Persona Type	Segment Characteristics Summary	Assigned Persona	Overall Proportion	Number ($N = 381$)
Group 1	Health-oriented factor, high cooking motivation factor		17%	64
Group 2	Regular cooking factor, strong self-management factor		10%	38
Group 3	Function improvement factor, balanced nutrition factor		13%	49
Active Persona Word Cloud		Health-active	40%	152
Group 4	Myopia + cooking assistance		28%	106
Group 5	Process-dependent + cooking assistance		6%	22
Conservative Persona Word Cloud		Low-vision	34%	129
Group 6	Cooking experience-oriented	Experience-oriented	14%	53
Group 7	Novelty + fun cooking		12%	46

Experience Persona Word Cloud		Experience-oriented	26%	99

Based on the factor scores obtained from the cluster analysis (as summarized in Table 5), the study employed K-means clustering in SPSS to categorize the sample according to lifestyle. By combining user demographic statistics with dietary behavior data, seven distinct groups were identified (see Table 8). Groups 1, 2, and 3: Health-oriented active users (40.0%) – These users have clear health goals and strong self-management abilities. Groups 4 and 5: Conservative cooking users (26.0%) – These users are willing to try new healthy diets and cooking methods. Groups 6 and 7: Experience-oriented users (25.9%) – These users treat healthy cooking as a recreational activity and prefer gamified, highly interactive cooking experiences. The word cloud visualization was generated using a Word Cloud generator by importing keywords and their proportional frequencies to create the tag list as shown in Table 8.

5. User persona presentation and design strategy development

5.1. Interface visualization design strategy

The product system should determine the user's intent based on their current context and multimodal behaviors, such as eye movement, emotional expressions, gestures, facial expressions, and body language, and provide appropriate feedback through multimodal outputs including interface visuals, lighting effects, voice, and haptics. For the health-active user persona, the AR interactive interface is designed using interface visualization and information overlay strategies to improve the efficiency and accuracy of obtaining product information, understanding the context, and making decisions. By recording and collecting users' purchase data from fresh produce apps or physical platforms—including vegetables, meats, and other items—the system can analyze historical recipe preferences, cooking frequency, and reviews to infer taste tendencies and cooking habits.

The AR interface visualization system presents product information—especially for vegetables—through panoramic projection, transparent images, or video, showing details such as origin, harvest time, shelf life, farmer information, pesticide residue reports, and organic certification. When users select a product, the UI displays star ratings, user reviews, and sales rankings, assisting users in making informed purchase decisions. This approach seamlessly integrates digital information with the physical environment, allowing users to perceive and process information more intuitively, reducing cognitive load, and optimizing the home cooking and shopping experience.

5.2. Design strategy for low-vision users

Among the conservative-type users, over 80% are low-vision users wearing glasses. These users face increased cognitive load or restricted visual input when using AR glasses during cooking tasks, requiring additional mental resources to compensate. This increased cognitive demand not only affects task performance but may also create safety risks and emotional burden. For such users, the design incorporates voice-guided assistance to provide step-by-step reminders, real-time progress tracking, and error correction prompts. Interfaces with voice feedback or high-contrast displays support low-vision users in interacting safely and efficiently with kitchen tools, reducing the risk of errors and facilitating a smoother cooking experience.

5.3. Narrative experience-oriented design strategy

The experience-oriented user persona benefits from a narrative design strategy that guides users to achieve pleasure, meaning, and immersion during interactions, enhancing engagement and achieving design goals. This strategy centers users within a narrative structure, with virtual chefs or assistants in the AR interface guiding them through the cooking process. Safety prompts appear when users approach hazards such as open flames or sharp knives; positive feedback is provided for correct operations, and corrective guidance is issued for errors, ensuring safe and smooth cooking. Upon completion, the system generates an AR visualization of the finished dish, allowing users to share it with friends and increasing social satisfaction and the likelihood of repeated use. This triad of strategies—interface visualization, low-vision support, and narrative experience design—collectively constructs a user-centered AR intelligent kitchen framework tailored to the differentiated needs of home cooking user personas.

6. Conclusion

Home intelligent kitchen practices play an irreplaceable and positive role in the nutritional health of Chinese residents. Against the backdrop of dietary structure transitions and the high prevalence of chronic diseases in China, home fresh-cooking is an important pathway for realizing the "Healthy China" strategy. This study constructs user personas for home cooking groups through quantitative research methods and derives differentiated experience design optimization strategies for intelligent kitchens. Future research should continue to explore how technological innovation, nutrition education, and policy guidance can further enhance the health benefits and adoption of home cooking, as well as investigate its application and optimization strategies across different regions and user groups. Additionally, integrating cutting-edge concepts such as embodied cognition, context awareness, and distributed design to develop intelligent home cooking education and dietary management applications can help embed healthy eating behaviors into daily life, making health management more engaging, enjoyable, and sustainable.

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