

AN INTEGRATED FRAMEWORK FOR USER-REQUIREMENT-DRIVEN DESIGN OPTIMIZATION OF UNMANNED VENDING VEHICLES

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Abstract - The rapid development of intelligent retail technologies has promoted the application of unmanned vending vehicles in increasingly diverse service environments. However, existing studies have primarily focused on autonomous navigation, sensing, and functional implementation, while paying insufficient attention to the systematic translation of user requirements into design specifications. To address this limitation, this study develops an integrated framework for extracting, prioritizing, and transforming the design requirements of unmanned vending vehicles by combining Grounded Theory, the KANO model, the Analytic Hierarchy Process (AHP), and Quality Function Deployment (QFD). Semi-structured interviews were conducted with 20 participants who had experience using unmanned vending devices or related intelligent self-service retail systems. Grounded Theory analysis generated 472 free nodes, 39 initial categories, 14 main categories, and four core dimensions: functional needs, shopping experience needs, safety needs, and design style needs. Subsequently, 462 questionnaires were distributed, and 406 valid responses were obtained. The KANO analysis classified six requirements as must-be qualities, four as one-dimensional qualities, three as attractive qualities, and one as an indifferent quality. Better-Worse analysis and AHP were then used to determine the relative priorities of the user requirements. Finally, QFD transformed these requirements into 13 design elements and corresponding technical specifications. The cognitive load optimization model, micro-interaction experience engineering, and semantic interactive search system obtained the highest relative weights of 0.1646, 0.1428, and 0.0947, respectively. These findings indicate that operational convenience, interaction fluency, and search efficiency are more influential in improving user satisfaction than simply increasing functional complexity. The proposed framework provides a systematic approach for translating user needs into actionable design specifications and offers practical guidance for the user-centered development of unmanned vending vehicles and related intelligent retail products.

Keywords: Unmanned Vending Vehicles, Grounded Theory, KANO Model, Quality Function Deployment, User-Centered Design.

1. Introduction

Driven by rapid technological innovation, intelligent and automated technologies have increasingly penetrated multiple sectors of the global economy, resulting in substantial structural transformation within the retail industry [1]. Since the commercialization of computer technologies in the mid-twentieth century, retail systems have evolved through several stages, including electronic data interchange (EDI) [2] and enterprise resource planning (ERP) [3], eventually entering the current era of smart retail characterized by artificial

intelligence algorithms, ubiquitous Internet of Things (IoT) perception, and heterogeneous data integration [4]. In particular, the development of autonomous perception networks based on IoT technologies has accelerated the emergence of unmanned retail terminals capable of adaptive environmental interaction [5]. By integrating radio frequency identification (RFID), computer vision, and multimodal sensing technologies into embedded systems, these intelligent retail devices establish a closed-loop operational mechanism covering product identification, payment settlement, and inventory management, thereby facilitating the

transition of retail services from “human-machine collaboration” to fully autonomous operation [6].

As a representative form of intelligent retail infrastructure, unmanned vending vehicles have demonstrated significant technological progress through the integration of simultaneous localization and mapping (SLAM), multi-sensor fusion positioning, and biometric recognition technologies. Such developments have contributed to the establishment of dynamic supply-demand matching networks [7], improvements in commodity circulation efficiency [8], and optimization of user interaction processes [9]. In essence, this emerging retail model has shifted conventional retail logic toward a “goods-find-people” paradigm [10]. With the continuous advancement of artificial intelligence and autonomous driving technologies, the application scenarios of unmanned vending vehicles have gradually expanded beyond traditional commercial spaces such as shopping malls and airports to urban streets, campuses, and office environments, providing consumers with more flexible and efficient shopping experiences. Consequently, unmanned vending vehicles have attracted increasing attention as a novel retail service model with broad development potential.

Existing studies on unmanned vending vehicles primarily emphasize technological realization and functional optimization. Liu et al. proposed an improved artificial potential field method for path planning and trajectory tracking of logistics unmanned delivery vehicles. Their method improved obstacle avoidance, shortened the planned path, and enhanced vehicle stability in complex multi-obstacle environments [11]. Kabir H et al. explored the construction of IoT-based autonomous perception networks and investigated mobile robotic terminals with environmental adaptability [12]. Liu L et al. developed a binocular vision scheme combined with an improved neural network algorithm, enhancing both detection accuracy and inference efficiency for intelligent vending applications [13]. Although these studies provide important technical support for the advancement of unmanned retail systems, excessive emphasis on technological implementation may weaken the connection between products and actual user expectations. Adeleke A G et al. argued that user-centered design plays a critical role in ensuring that technological innovation remains aligned with practical user needs [14]. In the relatively limited body of design-oriented research, Yan M et al. applied industrial design and interaction design approaches to develop an intelligent driverless food truck prototype and further analyzed user scenarios, operational procedures, and information presentation strategies [15]. Nevertheless, these studies still rely predominantly on quantitative analysis and pay insufficient attention to users’ latent needs and emotional expectations. Previous

research on self-service technologies in retail environments has shown that perceived ease of use, reliability, usefulness, and interaction experience are key factors shaping users’ attitudes toward such systems and their satisfaction with the shopping process [16]. This suggests that the successful implementation of unmanned retail products depends not only on technical functionality but also on whether the interaction process is understandable, reliable, and consistent with users’ actual behavioral expectations.

To address these limitations, this study proposes a systematic framework for the user-centered design optimization of unmanned vending vehicles by integrating Grounded Theory, the KANO model, the Analytic Hierarchy Process (AHP), and Quality Function Deployment (QFD). Grounded Theory is employed to identify latent user requirements and organize them into a structured requirement system through qualitative data analysis [17]. The KANO model is then used to classify the identified requirements according to their different effects on user satisfaction [18], while AHP supports the evaluation of their relative importance from a professional perspective. Finally, QFD is applied to establish the relationships between prioritized user requirements and corresponding design and technical considerations [19]. Through this sequential process of requirement identification, classification, weighting, and transformation, the study aims to reduce the disconnection between user research and design decision-making. The proposed framework provides a systematic methodological basis for the design optimization of unmanned vending vehicles and may also offer useful references for the development of related intelligent retail products.

2. Theoretical Research

2.1 Grounded Theory

Grounded Theory is a qualitative research methodology that emphasizes theory generation through systematic data collection and analysis rather than validating predefined hypotheses [20]. The method focuses on identifying latent patterns, behavioral motivations, and relationships from empirical data through continuous comparison and interpretation [21]. In practical research, Grounded Theory commonly adopts three coding stages, including open coding, axial coding, and selective coding, as shown in Table 1. Through these procedures, researchers are able to extract key concepts from qualitative data and gradually construct a structured theoretical framework [22].

The application of Grounded Theory in this study is mainly based on its exploratory and flexible characteristics in dealing with emerging and complex research contexts. Since unmanned vending

vehicles are still in the developmental stage, existing theories are insufficient to comprehensively explain users' behavioral preferences and interaction expectations. Grounded Theory therefore provides an appropriate approach for identifying user demands directly from empirical data rather than relying solely on predefined assumptions [23]. Previous studies have demonstrated the effectiveness of Grounded Theory in uncovering latent demand structures and behavioral patterns across different research domains [24–25]. For example, Yin J et al. applied Grounded Theory to analyze tourism development practices and stakeholder perceptions in Beishan Village, Zhuhai, and proposed optimization strategies for integrated urban-rural development [25]. Wang YaLi et al. employed three-level coding to extract stylistic characteristics of Ming Dynasty furniture and summarized the underlying design patterns [26]. Zhang JX et al. combined text mining and Grounded Theory to identify consumer demands for museum blind-box cultural products and further explored sustainable design strategies [27].

Table 1. The three steps of Grounded Theory

Coding Stage	Details
Open Coding	The data is analyzed line by line to identify various patterns, themes and concepts within it, which are then categorized and named.
Axial Coding	The researcher organizes and summarizes the relationships among the identified patterns and themes to create a more systematic and coherent coding framework.
Selective Coding	The most representative and important codes are selected and analyzed in order to dig deeper into the intrinsic meanings and connections to support the final theory construction.

Although Grounded Theory enables researchers to obtain detailed and in-depth user insights, the method itself does not directly determine the hierarchical importance of different user requirements. Therefore, in this study, Grounded Theory is primarily employed to identify users' experiences, expectations, and improvement demands regarding unmanned vending vehicles, thereby providing a qualitative foundation for the subsequent application of the KANO model.

2.2 KANO Model

The KANO model, proposed by Noriaki Kano in the 1980s, is widely used to analyze the relationship between product attributes and user satisfaction [28]. By categorizing user requirements into different levels, the model helps identify which features have the greatest influence on user perception and satisfaction [29]. In this study, user requirements are classified into five categories: Must-be Quality, One-dimensional Quality, Attractive Quality, Indifferent Quality, and Reverse Quality, as shown in Table 2. This classification framework enables researchers to distinguish between essential functions and additional value-added features, thereby supporting more targeted design optimization.

Previous studies have demonstrated the applicability of the KANO model in product and service design research. Qiang Wei et al. applied the KANO model to categorize user requirements for a maternal and infant desktop sterilizer and further transformed key requirements into feasible design solutions [30]. Ge et al. used the KANO model to identify the hierarchical needs of self-care elderly users for smart toilets [31]. Similarly, the model has also been applied in the optimization of indoor temporary rest furniture by clarifying different demand levels and corresponding design priorities [32]. These studies indicate that the KANO model is effective in identifying differentiated user needs and supporting resource allocation in product development.

Table 2. KANO Requirement attributes

Causality	Description of Content	Representative Symbol
Must-be Quality	These needs are the basic expectations of the user of a product or service, and if they are not met, the user is dissatisfied, but when they are met, they do not increase the user's satisfaction.	M
One-dimensional Quality	These are needs of which the user is explicitly aware and for which satisfaction is directly proportional to the degree to which the product or service is provided.	O
Attractive Quality	These needs are features that the user is not expecting but are present in the product or service and will surprise the user and provide additional satisfaction.	A
Indifferent Quality	These needs are aspects of the product or service features that the user does not care about and will have no impact on user satisfaction whether they are provided or not.	I
Reverse Quality	These needs are features that users do not want in the product or service, and when the product or service has them, they will instead reduce user satisfaction.	R

In the context of this study, the KANO model is employed to classify the user requirements of unmanned vending vehicles and evaluate their relative influence on user satisfaction. As noted by Wolniak, user expectations are dynamic, and features initially regarded as attractive may gradually evolve into expected or even basic requirements as technologies and market conditions develop [33]. This dynamic characteristic makes the KANO model particularly suitable for the continuous optimization of intelligent products. However, although the KANO model effectively distinguishes requirement priorities, it does not directly provide guidance for translating user demands into specific technical solutions. Therefore, this study further introduces the QFD method to establish the relationship between user requirements and concrete design elements, thereby enhancing the practicality and feasibility of the overall design optimization process.

2.3 Overview of QFD Theory

Quality Function Deployment (QFD) is a systematic methodology used to translate customer requirements into specific product design and technical specifications, thereby ensuring that product development aligns with user expectations [34]. The core concept of QFD is to transform the Voice of the Customer (VOC) into actionable technical requirements and integrate them into different stages of product development and engineering design [35]. In practical applications, QFD is commonly implemented through the "House of Quality," which establishes the relationship between customer needs and technical characteristics in a matrix form. Through evaluation and prioritization within the matrix, key technical requirements can be identified to support product optimization.

Previous studies have demonstrated the effectiveness of QFD in requirement transformation and design optimization. Li et al. applied QFD to integrate the functional requirements of elderly users for home blood glucose meters into specific product and service design elements [36]. Tsang et al. used QFD to translate tourists' expectations regarding smart tourism experiences into concrete technical design requirements, thereby strengthening the connection between user expectations and intelligent service systems [37]. These studies indicate that QFD is effective in bridging the gap between user demands and technical implementation while improving the feasibility and accuracy of design decisions.

In this study, QFD is employed to transform the requirement categories identified through the KANO model into specific design elements and technical requirements for unmanned vending vehicles. By establishing the relationship between user demands

and technical characteristics, the QFD model provides a structured basis for design optimization and supports the development of more user-oriented intelligent retail products.

2.4 Building a Research Framework

This study integrates Grounded Theory, the KANO model, Better–Worse analysis, the Analytic Hierarchy Process (AHP), and Quality Function Deployment (QFD) to construct a systematic framework for user requirement analysis and design optimization of unmanned vending vehicles. These methods are organized according to their complementary functions rather than being applied as a simple combination of analytical tools. The overall research process consists of three interrelated stages.

In the first stage, Grounded Theory is employed to identify users' latent needs, behavioral concerns, and experiential expectations through interview data collection and qualitative coding analysis. Open coding, axial coding, and selective coding are used to transform the original interview materials into a structured user requirement system, thereby providing an empirical foundation for the subsequent quantitative analysis.

In the second stage, the KANO model is applied to classify the identified requirements according to their different effects on user satisfaction. Better–Worse analysis is then used to quantify the extent to which the presence or absence of each requirement influences satisfaction and dissatisfaction. On this basis, AHP incorporates expert judgments to evaluate the relative importance of the requirements from a professional perspective. The combination of user-based assessment and expert-based evaluation provides a more comprehensive basis for determining design priorities.

In the third stage, QFD is used to translate the prioritized user requirements into corresponding design elements and technical requirements. Through the House of Quality, the relationships between user needs and product characteristics are systematically established, enabling the identification of key design directions and supporting subsequent design decision-making.

Through this sequential integration, Grounded Theory addresses the identification of user requirements, the KANO model and Better–Worse analysis clarify requirement attributes and satisfaction effects, AHP supports importance evaluation, and QFD completes the transformation from prioritized requirements to design-oriented technical elements. The proposed framework therefore establishes a continuous and traceable process of requirement identification, attribute classification, importance evaluation, and design transformation, as shown in Figure 1.

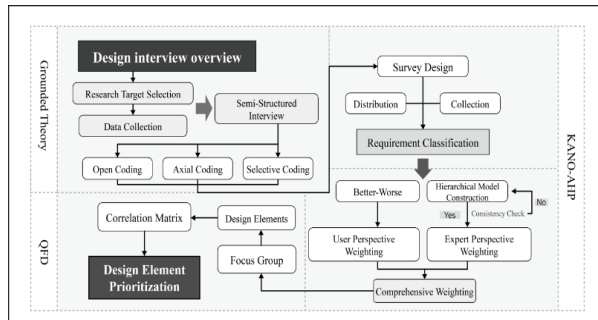


Figure 1: Research Flowchart

3. User Needs Analysis Based on Grounded Theory

3.1 Constructing interview outlines and user research

User requirement analysis based on Grounded Theory is the starting point of the whole unmanned vending vehicle design optimization process. As mentioned earlier, Grounded Theory, as a qualitative research method, can help researchers generalize

potential user needs from actual data rather than relying on theoretical assumptions or a priori knowledge. Grounded Theory enables an in-depth understanding of users' actual needs and expectations, thereby providing a solid foundation for the subsequent classification of requirements and extraction of design elements.

In order to ensure the comprehensiveness and representativeness of data collection, an interview outline capable of exploring users' needs in a comprehensive manner is designed through searching for relevant information and internal discussions within the team. In designing the interview outline, the research team identified several key topic areas based on the functional characteristics of unmanned vending vehicles, including users' functional expectations, usage scenarios, operational experiences, product appearance, interaction design, and acceptance of intelligent technologies. Selected questions from the interview outline are presented in Table 3.

Table 3. Overview of Interview Outlines

No.	Interview outline content
1	Have you ever used an unmanned vending vehicle? How was the experience?
2	What are the features you are most concerned about when using unmanned vending vehicles?
3	What is the most common problem you encountered when using unmanned vending vehicles?
4	Do you have any suggestions for the operation interface of unmanned vending vehicles?
5	What do you like about the appearance of unmanned vending vehicles?
6	What smart features have you been interested in or dissatisfied with during your use of unmanned vending vehicles?
.....	

After the interview outline was finalized, purposive sampling combined with random recruitment was adopted to ensure diversity in participant backgrounds and improve the representativeness of the qualitative data. Prior to the interviews, all participants were informed of the operational characteristics and application scenarios of unmanned vending vehicles to establish a consistent understanding of the research context. Semi-structured interviews were subsequently conducted because this method allows researchers to flexibly adjust the sequence and depth of questions according to participants' responses, thereby facilitating a deeper exploration of users' perceptions, behavioral expectations, and latent concerns regarding intelligent retail services [38].

Considering the geographically dispersed distribution of participants, most interviews were conducted online. All interview data were collected with participants' informed consent, and the interview process was recorded and transcribed for subsequent analysis. Each interview lasted

approximately 25–40 minutes and was conducted between September and November 2024. During the interviews, follow-up questions were introduced when necessary to further investigate participants' attitudes toward operational convenience, interaction logic, safety perception, product appearance, and intelligent service experience associated with unmanned vending vehicles.

To improve the richness and reliability of the data, this study expanded the interview sample to 20 participants from different age groups, educational backgrounds, and occupational categories. Among them, 11 participants were male and 9 were female, ranging in age from 19 to 61 years old. All participants had prior experience using unmanned vending devices or related intelligent self-service retail systems, such as smart vending machines, self-checkout terminals, or mobile intelligent retail equipment. The inclusion of users with diverse usage experiences and professional backgrounds enabled the study to capture a broader range of practical feedback and user expectations regarding unmanned

vending vehicles. Detailed participant information is presented in Table 4.

According to the requirements of Grounded Theory research, theoretical saturation rather than sample quantity alone serves as the key criterion for determining the adequacy of qualitative data [39]. Therefore, after the completion of the initial coding process, the research team continuously compared newly collected interview data with existing categories through iterative coding and constant comparative analysis.

Open coding, axial coding, and selective coding were

independently conducted by multiple researchers to improve coding consistency and analytical reliability. During the later stage of analysis, saturation testing was performed using the final interview samples. The results indicated that no substantially new concepts, categories, or relational patterns emerged from the additional interview data, suggesting that the core conceptual framework had reached theoretical saturation. Consequently, the interview data were considered sufficient to support the subsequent requirement extraction and design optimization analysis.

Table 4. Information of Interviewees

No.	Sex	Age	Education Level	Occupation	Experience with Unmanned Vending Devices
1	Male	35	Bachelor's Degree	Office Employee	Yes
2	Male	28	Master's Degree	Graduate Student	Yes
3	Female	42	High School Degree	Housewife	Yes
4	Male	53	High School Degree	Laborer	Yes
5	Female	19	High School Degree	Student	Yes
6	Female	23	Bachelor's Degree	Student	Yes
7	Male	36	Master's Degree	Teacher	Yes
8	Female	45	Doctoral Degree	Professor	Yes
9	Female	58	Bachelor's Degree	Bank Clerk	Yes
10	Male	43	Doctoral Degree	Teacher	Yes
11	Female	27	Master's Degree	Engineer	Yes
12	Male	29	Bachelor's Degree	IT Technician	Yes
13	Female	31	Master's Degree	Sales Manager	Yes
14	Male	22	High School Degree	Courier	Yes
15	Female	38	Bachelor's Degree	Designer	Yes
16	Male	26	Bachelor's Degree	Retail Staff	Yes
17	Female	61	High School Degree	Retired Worker	Yes
18	Male	33	Master's Degree	Product Manager	Yes
19	Female	25	Bachelor's Degree	Media Practitioner	Yes
20	Male	47	Bachelor's Degree	Logistics Supervisor	Yes

3.2 Coding Process

• Open Coding

Open coding represents the initial stage of Grounded Theory analysis and focuses on conceptualizing and categorizing raw qualitative data without relying on predetermined theoretical assumptions [40]. In this study, all interview transcripts were repeatedly reviewed and independently coded by multiple members of the research team to improve analytical reliability. During the coding process, researchers conducted line-by-line and sentence-by-sentence analysis of the interview content, extracting representative expressions, behavioral descriptions, and experiential perceptions related to unmanned vending vehicle usage. The extracted concepts were then continuously compared, merged, and refined through group discussion to form preliminary conceptual categories.

Based on the coding results of the 20 interview samples, a total of 472 free nodes were initially identified. After repeated comparison, integration, and elimination of overlapping concepts, 39 initial categories were ultimately generated, as shown in Table 5. These categories primarily reflected users' concerns regarding operational convenience, interaction experience, safety perception, product display, intelligent functions, and appearance design. The purpose of the open coding stage was not only to identify explicit user requirements but also to uncover latent expectations and potential behavioral motivations embedded within users' experiences and perceptions.

To improve the credibility of the analysis, the coding process adopted a constant comparative approach in which newly extracted concepts were continuously compared with previously established categories. When inconsistencies occurred, the research team conducted iterative discussions and

re-examined the original interview materials until consensus was reached. Through this process, the study was able to capture the diversity and complexity

of user demands while establishing a reliable conceptual foundation for the subsequent axial coding and selective coding stages.

Table 5. Initial coding process of user interviews

Raw data	Initial Scope
The reliability of the positioning system has a direct impact on my trust in unmanned vending vehicles	Positioning systems
Understanding the traffic conditions on the road in order to choose the quickest route.	Real-time traffic information
I think the user interface design of the unmanned vending vehicle should be intuitive and clear.	User Interface Design
Payment habits and needs of different user groups should be taken into account	Settlement system
Do unmanned vending vehicles take into account the needs of the elderly and children?	Accessibility
I think the product categorization and filtering of the unmanned vending vehicle should be clear and straightforward	Product categorization and screening
I hope it can make full use of the space and be neatly and clearly arranged.	Shelf design
I think the billing system of the unmanned vending vehicle should support multiple payment methods	Multiple payment methods support
Quick operation directly affects my shopping efficiency and experience.	Quick operation
I think the unmanned vending vehicle should be able to monitor various risk factors.	Intelligent alarm system
The overall impression and visual effect of the unmanned vending vehicle, I want it to be attractive, comfortable and beautiful.	Body Ratio
I want it to capture my attention with a vibrant color scheme.	Color proportion balance
I want it to provide clear categorized signage and clear pathfinding.	Cargo classification system
The unmanned vending vehicle should display a variety of information about the products.	Goods description and specification
I want the unmanned vehicle to provide multiple after-sale channels.	After-sales service channels
The design of the vehicle structure should take into account the applicability and safety in different environments and scenarios.	Vehicle Structure Design
The unmanned vehicle should be able to integrate and harmonize with its surroundings in different environments.	Environmental Adaptation
It should be able to detect and avoid obstacles on the road in a timely manner.	Obstacle avoidance technology
I will refer to the reviews and ratings of other users to decide whether to buy the goods from the unmanned vending vehicles	User evaluation and rating
Face recognition or fingerprint recognition to confirm the user's identity to protect shopping safety and personal privacy.	User authentication mechanisms
Whether in hot summer or cold winter, the goods can be guaranteed to be fresh and safe.	Temperature control devices
The layout design should be clean and clear, easy to navigate and select.	Display layout design
I think it is able to give clear and unambiguous error alerts in a timely manner.	Error indication and correction mechanisms
I think interior design details should focus on detail and texture.	Interior design details
I think the cargo positioning technology can improve the convenience and satisfaction of shopping.	Cargo Positioning Technology
Being able to monitor the running status of the vehicle and the sale of goods in real time is needed for merchants.	Remote monitoring systems
The impression at the first sight of the vehicle can reflect the quality and image of the vehicle intuitively	Overall profile
I want to be able to find what I need quickly and accurately	Product search function
I believe that businesses should emphasize the timeliness of their customer service response.	Timely customer service response

The proper use of color can enhance my attraction and comfort to the product.	Color psychology
The stability and safety of the vehicle should be improved in complicated road conditions.	Anti-skid control system
The security and privacy of my payment information should be protected	Payment Security
I want unmanned vending vehicles to have the ability to respond quickly	Speed of response
I would like to be able to provide timely help and support in case of unexpected situations or emergencies	Emergency Assistance Service
Decorative strips and chrome pieces can add to the vehicle's texture and upscale feel	Decorative strips and chrome parts
I believe that personalization can provide users with a unique shopping experience.	Personalization
I want to protect the equipment and goods inside the vehicle from damage when using it outdoors.	Waterproof and dustproof design
Merchants can keep abreast of users' needs and opinions by collecting their feedback and suggestions	User feedback collection and analysis
I think the operation process should be simplified as much as possible to reduce the operation burden of users	Easy-to-understand operation process

• Axial Coding

Axial coding is the creation of associations and logical relationships between initial concepts and subcategories according to certain rules or paths through cluster analysis [41]. At this stage, instead of just extracting data, the focus is on understanding the intrinsic connections between different categories. By identifying conditions, contexts, and consequences, the research team establishes connections between concepts, which in turn leads to the construction of a structured theoretical framework. Specifically, the data were initially organized and categorized according to the research objectives and questions, and then the relationships and intrinsic meanings between the data were analyzed in depth by creating axes to connect the different categories. In this study, the 39 initial categories obtained through open coding were further refined into 14 representative main categories, as shown in Table 6. These categories constitute the principal user requirements for unmanned vending vehicles.

• Selective Coding

Selective coding is the construction of a comprehensive theoretical framework by focusing all concepts and categories on one or a few core categories [42]. The result of selective coding is the formation of a complete and systematic theoretical model that can effectively explain user needs and behavioral patterns. That is to say, the comparison of the main categories reveals the core categories that have an overarching role, thus clarifying the relationship between the core categories and the other categories, and further reflecting the prototype of the constructed theory. In this study, the main categories are further summarized into four core categories, which are functional needs, shopping experience needs, safety needs, and design style, see Table 6. Through this coding process, Grounded Theory provides a structured basis for analyzing user requirements for unmanned vending vehicles, enabling the study to examine these requirements from multiple dimensions and provide clearer guidance for subsequent design optimization.

Table 6. Category refinement process

Core Scope	Main Scope	Initial Scope
Functional Needs A1	Route Planning B1	Positioning System C1
		Real-time traffic information C2
		Obstacle avoidance technology C3
	Cargo Management B2	Cargo classification system C4
		Shelf design C5
		Temperature control devices C6
		Cargo Positioning Technology C7
	Commodity Selection B3	User interface design C8
		Display Layout Design C9
		Product search function C10
	Payment System B4	Multiple Payment Methods Support C11
		Settlement System C12
		Payment Security C13
	User Experience B5	Response Speed C14
		Accessibility C15
		Personalization C16

Shopping Experience Needs A2	Operation Convenience B6	Easy-to-understand operation processC17
		Error alert and correction mechanismC18
		Quick operation C19
	Commodity display B7	Product descriptions and specificationsC20
		User reviews and ratingsC21
		Product categorization and filteringC22
	After-sales service support B8	Customer service response timelinessC23
		After-sales service channelsC24
		User feedback collection and analysisC25
Safety Demand A3	Anti-theft and anti-loss design B9	Remote monitoring systemC26
		Waterproof and dustproof designC27
		User authentication mechanismC28
	Vehicle Stability B10	Vehicle Structure Design C29
		Anti-skid control systemC30
	Emergency ResponseB11	Emergency Rescue Service C31
		Intelligent Alarm SystemC32
Design Style A4	Appearance DesignB12	Vehicle Body Scale C33
		Overall Contour C34
	Color MatchingB13	Color Ratio Balance C35
		Color Psychology C36
		Environmental AdaptabilityC37
	Detailed treatmentB14 Main Scope	Interior Design DetailsC38
		Decorative strips and chrome partsC39

Based on the Grounded Theory analysis, users' demands for unmanned vending vehicles can be summarized into four dimensions: functionality, shopping experience, safety, and design style. Functional requirements reflect users' expectations regarding product performance, operational reliability, and shopping efficiency, highlighting the importance of satisfying practical usage demands [43]. Shopping experience requirements indicate that users not only focus on functional realization but also value convenience, comfort, and interaction quality throughout the shopping process [44]. Safety requirements emphasize the importance of maintaining user trust and product reliability in different usage scenarios. In addition, design style requirements suggest that visual attractiveness and aesthetic consistency can positively influence user perception, brand recognition, and overall product competitiveness [45]. These findings provide a clearer direction for subsequent design optimization by identifying the core aspects that users are most concerned about in unmanned vending vehicle systems.

4. User Requirements Segmentation Based on KANO Model

4.1 Questionnaire Research and Data Organization

Based on the Grounded Theory analysis, 14 main categories (B1–B14) were identified as the principal user requirements for unmanned vending vehicles. These categories represent the key concepts derived from the qualitative data and provide the basis for

the subsequent classification and evaluation of user requirements [46]. Accordingly, a KANO questionnaire was developed to examine users' perceptions of the 14 requirements. For each requirement, a pair of functional and dysfunctional questions was designed to assess users' responses when the corresponding feature was provided and when it was not provided. Each question contained five response options: "I like it that way," "It must be that way," "I am neutral," "I can live with it that way," and "I dislike it that way" [47]. The paired responses were not assigned numerical scores; instead, they were matched using the KANO evaluation table to classify each requirement as Must-be (M), One-dimensional (O), Attractive (A), Indifferent (I), Reverse (R), or Questionable (Q).

To ensure the statistical reliability and representativeness of the questionnaire survey, the required sample size was estimated prior to questionnaire distribution under a 95% confidence level. The sample size calculation was conducted using the formula (1).

$$n = \frac{Z^2 p(1-p)}{e^2} \quad (1)$$

where n represents the required sample size, Z is the Z-score corresponding to the confidence level, p represents the estimated population proportion, and e denotes the acceptable margin of error. In this study, a 95% confidence level was adopted (Z = 1.96), while the population proportion was conservatively set at p = 0.5 to maximize sample variability. The acceptable margin of error was controlled within 5% (e = 0.05). Based on the

calculation, the minimum required sample size was approximately 384.

Considering the possibility of incomplete responses, invalid questionnaires, and data screening during the survey process, the actual number of distributed questionnaires was intentionally increased beyond the minimum sample requirement to improve data reliability and ensure sufficient valid samples for subsequent analysis. Therefore, a total of 462 questionnaires were distributed. After data collection and screening, 423 questionnaires were returned, among which 406 valid questionnaires were ultimately retained after excluding incomplete, inconsistent, or invalid responses. The effective response rate was 87.9%.

Since the final valid sample size exceeded the minimum required threshold, the questionnaire data were considered to possess acceptable statistical representativeness and reliability for subsequent KANO classification, weighting analysis, and user demand evaluation.

In addition, the sample included participants with diverse demographic characteristics in terms of gender, age, educational background, and occupation, thereby improving the diversity of the survey data, as shown in Table 7.

A total of 462 questionnaires were distributed, 423 were collected, and 406 valid questionnaires were obtained after sifting out the problem questionnaires. The effective recovery rate of the questionnaires was 87.9%, of which 58% were male and 42% were female, and their ages ranged from 23 to 52 years old. In order to better understand the user feedback, the recovered questionnaires were organized according to the form of Table 8, and a user needs classification table was obtained, see Table 9. According to the KANO evaluation results, B1, B2, B4, B6, B7, and B10 were classified as Must-be Requirements (M); B3, B5, B8, and B11 were classified as One-dimensional Requirements (O); B12, B13, and B14 were classified as Attractive Requirements (A); and B9 was classified as an Indifferent Requirement (I).

Table 7. Demographic Profile of Questionnaire Respondents

Category	Classification	Frequency (N)	Percentage (%)
Gender	Male	235	57.9
	Female	171	42.1
Age	23–29 years old	118	29.1
	30–39 years old	146	36.0
	40–49 years old	97	23.9
	50–52 years old	45	11.0
Education Level	High School or Below	72	17.7
	Bachelor's Degree	201	49.5
	Master's Degree	103	25.4
	Doctoral Degree	30	7.4
Occupation	Student	74	18.2
	Office Employee	102	25.1
	Technical/Engineering Staff	61	15.0
	Sales and Service Industry	58	14.3
	Education/Research Personnel	47	11.6
	Self-employed/Freelancer	36	8.9
	Other Occupations	28	6.9
Experience with Intelligent Self-service Retail Devices	Frequently Used	154	37.9
	Occasionally Used	187	46.1
	Rarely Used	65	16.0

Table 8. KANO Demand Classification Table

Requirement	Not available for this requirement					
Provide this requirement		Like	That's the way it should be	Doesn't matter	I can live with it	I don't like it
	Like	Q	A	A	A	O
	That's the way it should be	R	I	I	I	M
	Doesn't matter	R	I	I	I	M
	I can live with it	R	I	I	I	M
	I don't like it	R	R	R	R	Q

Table 9. Data Compilation of KANO Questionnaire

No.	M (%)	O (%)	A (%)	I (%)	R (%)	Form
B1	33.1	21.3	18.5	22.7	4.4	M
B2	31.8	22.6	25.4	19.5	0.7	M
B3	22.9	32.5	21.3	23.3	0	O
B4	28.6	24.9	25.1	21.4	0	M
B5	21.4	34.5	21.8	22.1	0.2	O
B6	28.7	23.7	22.9	24.7	0	M
B7	30.4	23.3	21.9	24.4	0	M
B8	21.6	31.6	22.8	22.5	1.5	O
B9	20.3	19.8	21.7	35.6	2.6	I
B10	29.6	22.3	21.8	25.4	0.9	M
B11	23.1	29.3	24.6	22.4	0.6	O
B12	23.6	21.7	34.4	19.2	1.1	A
B13	23.6	22.1	32.2	22.1	0	A
B14	23.1	22.4	30.7	23.2	0.6	A

4.2 Better-Worse Coefficient Analysis

To further determine the importance of each specific requirement item, user requirements were prioritized using the Better-Worse coefficient, which was proposed by Charles Berger to quantitatively evaluate the extent to which an increase or decrease in a functional requirement affects user satisfaction [48]. Among them, Better coefficient can be understood as the satisfaction coefficient after increasing a certain demand element, and the value is usually positive, when the value is larger or closer to 1, it indicates that the stronger the satisfaction enhancement effect of the user when enhancing the related user demand, and the faster the satisfaction enhancement is. Worse coefficient indicates the dissatisfaction coefficient after eliminating a certain demand element, and the value is usually negative, when the value is smaller or closer to -1, it indicates that the stronger the dissatisfaction enhancement effect of the user when the relevant user requirement is not provided, and the faster the dissatisfaction enhancement. Therefore, among many user demand elements, the demand elements

with larger absolute values of Better coefficient and Worse coefficient should be prioritized to be satisfied [49]. The Better coefficient is calculated in equation (2) and the Worse coefficient is calculated in equation (3).

$$B_i = \frac{A+O}{A+O+M+I} \quad (2)$$

$$W_i = -1 * \frac{O+M}{A+O+M+I} \quad (3)$$

Taking the absolute value of the dissatisfaction index Worse and the satisfaction index Better as the horizontal and vertical coordinates, with their mean values as the critical lines of the horizontal and vertical coordinates, the center point of the coordinates is calculated using formulas (4) and (5) as $C_x = 0.51$, $C_y = 0.5$. Combining the center point with the B_i and W_i values of each demand, a four-quadrant scatter plot of the importance of various demands for the unmanned vending vehicle is drawn, as shown in Figure 2.

$$C_x = \frac{1}{n} \sum_{i=1}^n |W_i| \quad (4)$$

$$C_y = \frac{1}{n} \sum_{i=1}^n B_i \quad (5)$$

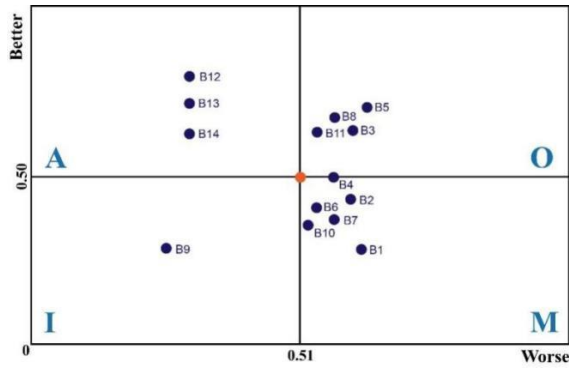


Figure 2: KANO Quadrant Diagram

In the Better-Worse coordinate system of the KANO model, each demand point has different B_i (Better) and W_i (Worse) values. However, simply looking at these values does not make it easy to intuitively compare the influence of each demand. Therefore, it is necessary to calculate the Euclidean distance from each demand point to the center point to more accurately present the priority relationships among various demands.

D_i represents the importance value of each demand item—the farther the distance, the higher the importance of the item within its category, and vice versa. Based on the calculation formula (6) for D_i , the importance values of the 14 requirements for the unmanned vending vehicle are obtained, and the priority ranking of each element within different demand categories is shown in Table 10.

$$D_i = \sqrt{(|W_i| - C_x)^2 + (B_i - C_y)^2} \quad (6)$$

Among them, D_i represents the distance between demand item i and the center of the coordinate axis, B_i represents the Better score of demand item i , and W_i represents the Worse score of demand item i . C_x and C_y are the horizontal and vertical coordinates of the center point of the coordinate axis, respectively. The higher the D_i value, the more significant its difference from the overall demand distribution, indicating that it may be a core demand that determines user satisfaction. Conversely, a lower D_i value suggests that the demand is more common and has a smaller impact on users.

Table 10. Weight of Each Attribute

Causality	Demand	B_i	W_i	D_i
M	B4	0.5	0.54	0.03000
	B2	0.48	0.55	0.04472
	B7	0.45	0.54	0.05831
	B6	0.47	0.52	0.03162
	B1	0.41	0.56	0.10296
	B10	0.45	0.52	0.05099
O	B5	0.57	0.56	0.08602
	B3	0.54	0.55	0.05657
	B8	0.55	0.54	0.05831
	B11	0.54	0.53	0.04472
A	B12	0.57	0.46	0.08602
	B13	0.54	0.46	0.06403
	B14	0.53	0.46	0.05831
I	B9	0.43	0.41	0.12207

Because the calculated Euclidean distances vary substantially across requirement categories, the values were normalized to reduce the influence of extreme values and improve the comparability of the weighting results. The subsequent weighting analysis focuses on the Must-be (M), One-dimensional (O), and Attractive (A) requirements, whereas the Indifferent Requirement (B9) is excluded because it has a limited effect on user satisfaction.

Because each demand hierarchy is a separate category, the same classification normalization process is performed in the normalization process. The data for the three demand categories (B1-B14) are calculated by applying Equation (7) and are shown in Table 11.

$$\omega_c = \frac{D_i}{\sum D_i} \quad (7)$$

Through the above formula, the satisfaction weight ω_c of each demand item is obtained, which reflects the impact of different demand items on user satisfaction. To ensure the relative comparison of different demand item weights, ω_c is normalized to obtain the normalized weight of core attributes, ω_B . ω_A , ω_M , and ω_O represent the user demand attributes A, M, and O, respectively. In the table, we uniformly use ω_B to represent the proportion value of attributes. Using formula (8),(9),(10).

$$\omega_A = \frac{D_i \sum_{i \in S_A} \omega_{c_i}}{D_i \sum_{i \in S} \omega_{c_j}} \quad (8)$$

$$\omega_M = \frac{D_i \sum_{i \in S_M} \omega_{c_i}}{D_i \sum_{i \in S} \omega_{c_j}} \quad (9)$$

$$\omega_O = \frac{D_i \sum_{i \in S_O} \omega_{c_i}}{D_i \sum_{i \in S} \omega_{c_j}} \quad (10)$$

Where S_M is the set of demands corresponding to attribute M, i.e., $S_M = \{B4, B2, B7, B6, B1, B10\}$. Similarly, S_A and S_O are the demand sets corresponding to attributes A and O. S is the set of all demand items, i.e., $S = \{B1, B2, B3, \dots, B14\}$, and ω_{C_i} is the weight of demand C_i . User demand attributes and user demands are two independent values. To more accurately assess the demand weight, a comprehensive weight calculation is performed.

The comprehensive weight takes into account both the importance of demand attributes, ω_B , and the impact of the degree of satisfaction on user satisfaction ω_C . This product helps more accurately evaluate the priority of each demand in actual design. Using formula (11), the user-driven user demand weight proportions are finally calculated, as shown in Table 11.

$$\omega_{KANO} = \omega_B * \omega_C \quad (11)$$

Table 11. Categorization of the Weighted Share of User-level Requirements

Causality	ω_B	Demand	ω_C	ω_{KANO}
M	0.41238	B4	0.09416	0.03883
		B2	0.14036	0.05789
		B7	0.18302	0.07547
		B6	0.09925	0.04093
		B1	0.32316	0.13327
		B10	0.16004	0.06610
O	0.31792	B5	0.35022	0.11134
		B3	0.23032	0.07322
		B8	0.23740	0.07547
		B11	0.18207	0.05788
A	0.26969	B12	0.41284	0.11134
		B13	0.30731	0.08288
		B14	0.27985	0.07547

4.3 AHP-Based Weight Acquisition

In the above, the KANO model was used to analyze the requirements of unmanned vending vehicles in a hierarchical manner from the user's point of view, clarifying the categories of each requirement and their degree of influence on user satisfaction. Although users are the direct users of the product and can provide real demand feedback

from the experience perspective, it is often difficult for them to accurately judge the technical feasibility, market competitiveness and realization cost of the demand, as shown in Table 12 [50]. Therefore, on the basis of user requirements analysis, the introduction of expert-level evaluation can weigh the importance of each requirement from a professional point of view and provide more scientific guidance for product optimization.

Table 12. Differences between user and expert evaluations

Evaluation Dimension	User Evaluation	Expert Evaluation
Points of Interest	Personal experience, emotional needs, intuition	Technical feasibility, market trends, product sustainability
Evaluation Method	Requirement classification (Must-be, One-dimensional, Attractive)	Demand weighting calculations (pairwise comparisons, quantifying importance)
Basis of Evaluation	Personal use scenarios, subjective perception	Industry experience, data analysis, market research
Impact on decision-making	Influence on user satisfaction, enhancement of usage experience	Influence design priorities, optimize resource allocation
Limitations	Unable to accurately assess the technical feasibility and realization cost of requirements	May not fully cover users' real needs

Analytic Hierarchy Process (AHP) is a mathematical method for multi-criteria decision making, proposed by Thomas L. Saaty. AHP decomposes a complex decision problem into multiple hierarchical levels and uses expert-based pairwise comparisons to calculate the relative importance of each factor, thereby providing a structured basis for decision-making. Due to its clear structure and rigorous calculation, AHP is widely used in engineering management, economic analysis, product design and other fields.

• Modeling the Hierarchy

The first step in AHP is to construct a hierarchical model, i.e., to decompose a complex decision problem into multiple levels for systematic analysis. A hierarchical structure usually includes a Top Level, a Criteria Level, an Alternative Level, or a sub-criteria level, which is used to systematically decompose the decision problem. This study combines the user requirements analyzed by the KANO model to refine the design optimization objectives of the unmanned vending vehicle into multiple key criteria. The objective level is the design optimization of unmanned vending vehicles. The criterion level comprises Must-be Requirements (M), One-dimensional Requirements (O), and Attractive Requirements (A), while the sub-criterion level consists of the 13 prioritized requirements, B1–B8 and B10–B14, as shown in Figure 3.

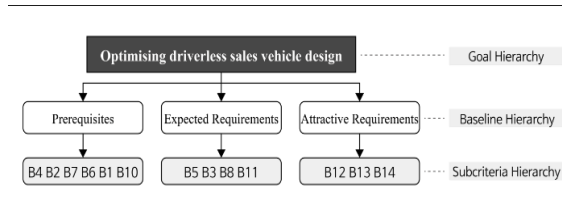


Figure 3: AHP hierarchical model

To scientifically assess the relative importance of each user requirement, pairwise comparison questionnaires were developed for the requirement categories identified through the KANO analysis. A total of 12 experts participated in the evaluation, including six academic researchers and six industry practitioners from the fields of product design, user experience, and emotional design. The experts were selected based on their relevant academic backgrounds and professional experience. All participants had substantial research experience in the related fields or more than five years of practical experience in product design and intelligent product development, enabling them to provide informed and systematic judgments. Before completing the questionnaire, the experts were introduced to the research objectives, the hierarchical structure of the evaluation indicators, and the basic principles of AHP. They were then asked to independently conduct pairwise comparisons of the requirement

items using Saaty's 1–9 scale, as shown in Table 13. All 12 questionnaires were completed and retained for the subsequent weighting and consistency analyses.

Table 13. Saaty Scale Values and Interpretation

Scale Value	Explanation
1	Two factors are equally important
3	One factor is slightly more important than the other
5	One factor is significantly more important than the other
7	One factor is very important, significantly more important than the other
9	One factor is extremely important, very significantly more important than the other
2,4,6,8	Values between the above levels are used to indicate that the importance of two factors is between the two ends of the scale

• Weights Solution

The expert judgment values obtained from the participating experts are used to calculate the data based on the following calculation steps in order to obtain the specific weighting values of the user requirements.

1) Normalize the matrix using the following formula:

$$\bar{a}_{ij} = a_{ij} / \sum_{i=1}^n a_{ij} (i, j = 1, 2, \dots, n) \quad (12)$$

Where a_{ij} represents the data in the i -th row and j -th column of judgment matrix A , and $\bar{a}_{ij}$ represents the data in the i -th row and j -th column of the normalized matrix.

2) Sum the elements within the matrix :

$$\bar{w}_i = \sum_{j=1}^n \bar{a}_{ij} (i, j = 1, 2, \dots, n) \quad (13)$$

3) Implement normalization for $\bar{w}_i$ in the above formula.

$$w_i = \bar{w}_i / \sum_{i=1}^n \bar{w}_i (i = 1, 2, \dots, n) \quad (14)$$

Where w_i represents the weight of the i -th criterion.

4) Compute the largest eigenvalue of the judgment matrix A .

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^n \frac{(Aw)_i}{w_i} \quad (15)$$

Where n is the order of the matrix, A is the judgment matrix, w_i is the weight of the i th indicator. λ_{max} is the maximum eigenvalue of the judgment matrix A .

Consistency test, for the vector obtained earlier, there are eigenvalues, consistency test, if you can pass the test, it means that the construction of the judgment matrix is reasonable, both the existence of the value of the interpretation. Assuming that CI stands for consistency index, the following is the arithmetic method:

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (16)$$

5) Consistency Ratio Calculation: The formula for calculating the consistency ratio CR is:

$$CR = \frac{CI}{RI} \quad (17)$$

Where RI is the average random consistency index, and its value varies depending on the order of the judgment matrix. In general, when $CR < 0.1$, the judgment matrix has satisfactory consistency; otherwise, the judgment matrix needs to be adjusted. The values of RI are shown in Table 14.

Table 14. RI Value

N	1	2	3	4	5	6	7	8
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41

The relevant expert evaluation values were calculated according to Equations (12)-(17), and a consistency test was conducted. The test yields that all values pass the consistency test ($CR < 0.1$), proving that the AHP weighting analysis is effective, and the specific values are shown in Table 15.

Table 15. Evaluation Indices for Must-be, One-dimensional, and Attractive Requirements

	M	O	A	ω_i	CR
M	1	2	3	0.54547	0.001
O	1/2	1	3/2	0.27272	
A	1/3	2/3	1	0.18181	

For the sub-criteria layer under the Must-be Requirements, including B4, B2, B7, B6, B1, and B10, the weights and consistency ratios calculated by AHP are shown in Table 16 below. Among them, B4 has the highest weight, implying that B4 (payment system) is the most important consideration in the Must-be Requirements, followed by B6 (ease of operation) and so on.

Table 16. Evaluation Indices for Must-be Requirements

	B4	B2	B7	B6	B1	B10	ω_j	CR
B4	1	3	5	2	4	6	0.38158	0.021
B2	1/3	1	3	1/2	2	4	0.16231	
B7	1/5	1/3	1	1/3	1/2	2	0.06922	
B6	1/2	2	3	1	3	5	0.23955	
B1	1/4	1/2	2	1/3	1	3	0.10367	
B10	1/6	1/4	1/2	1/5	1/3	1	0.04366	

For the sub-criteria layers B5, B3, B8, and B11 under the expectation-based requirements, the weights and consistency ratios obtained by using the AHP method are shown in the following Table 17. B5 (user experience) dominates the expectation-based requirements, and its weight is significantly higher than that of the other sub-criteria layers, which suggests that improving the user experience is crucial for meeting the user's expectations in the unmanned vending vehicle design.

Table 17. Evaluation Indices for One-dimensional Requirements

	B5	B3	B8	B11	ω_j	CR
B5	1	3	5	7	0.55790	0.044
B3	1/3	1	3	5	0.26334	
B8	1/5	1/3	1	3	0.12187	
B11	1/7	1/5	1/3	1	0.05689	

In the weighting analysis of B12, B13, and B14 under the Attractive Requirements, the results of the weights and consistency ratios obtained by applying AHP are shown in Table 18 below.

B12 has the highest weight, indicating that it has the greatest relative importance under this criterion, and it is a factor to focus on in the design optimization process.

Table 18. Evaluation Indices for Attractive Requirements

	B12	B13	B14	ω_j	CR
B12	1	3	4	0.62323	0.018
B13	1/3	1	2	0.23949	
B14	1/4	1/2	1	0.13729	

AHP usually contains several layers (target layer, criterion layer, sub-criterion layer), and the indicators in each layer may have their own local weights. In order to ensure the consistency of the expert decision-making system, these local weights were then converted into global weights relative to the highest level decision objectives, which were calculated based on Equation (18), resulting in Table 19.

$$\omega_{AHP} = \omega_i * \omega_j \quad (18)$$

Table 19. Combined weights of indicators

Demand Attributes	ω_i	Demand	ω_j	ω_{AHP}
M	0.54547	B4	0.38158	0.20814
		B2	0.16231	0.08856
		B7	0.06922	0.03776
		B6	0.23955	0.13067
		B1	0.10367	0.05655
		B10	0.04366	0.02382
O	0.27272	B5	0.55790	0.15215
		B3	0.26334	0.07182
		B8	0.12187	0.03324
		B11	0.05689	0.01552
A	0.18181	B12	0.62323	0.11331
		B13	0.23949	0.04354
		B14	0.13729	0.02496

4.4 Constructing Weighted Average Weights

In this study, the importance of user requirements based on the user is determined by the KANO model, and then the related requirement ranking is also obtained based on the expert level. In order to synthesize the opinions of users and experts, this paper uses a weighted average method to integrate the user-level and expert-level weights. Specifically, user weights and expert weights are given the same weight coefficient, i.e., 50% each. In this way, the importance of user needs and expert advice can be balanced to ensure that the final integrated weights reflect both the actual needs of users and the professional insights of experts, and the formula for the weighted average is shown in (19), and the results are shown in Table 20.

$$\omega_{SUM} = \omega_{KANO} * 0.5 + \omega_{AHP} * 0.5 \quad (19)$$

After obtaining the combined weights, this paper further analyzes the ranking and importance of each requirement under the combined weights. By comparing the results at the user level, the expert level, and under the composite weights, the impact of different weight assignments on the prioritization of requirements is explored. This helps to gain insights into the consistency and differences between users and experts in requirements assessment, and provides a more comprehensive perspective on the design decisions of unmanned vending vehicles. At the same time, the results of the comprehensive weighting also provide more reliable inputs for subsequent Quality Function Deployment (QFD)

analyses and optimization of design elements, ensuring that the design better meets user needs and reflects experts' professional recommendations.

Table 20. Combined Weighting of Users and Experts

Demand	ω_{KANO}	ω_{AHP}	ω_{SUM}	Sorted
B4	0.03883	0.20814	0.12349	2
B2	0.05789	0.08856	0.07323	6
B7	0.07547	0.03776	0.05662	9
B6	0.04093	0.13067	0.08580	5
B1	0.13327	0.05655	0.09491	4
B10	0.06610	0.02382	0.04496	12
B5	0.11134	0.15215	0.13175	1
B3	0.07322	0.07182	0.07252	7
B8	0.07547	0.03324	0.05436	10
B11	0.05788	0.01552	0.03670	13
B12	0.11134	0.11331	0.11233	3
B13	0.08288	0.04354	0.06321	8
B14	0.07547	0.02496	0.05022	11

5. QFD-Based Design Element Acquisition

5.1 Building a Quality House Model

As mentioned in the previous section, based on the Grounded Theory, the relevant user requirements are obtained through coding, and the KANO model divides the user requirements into attributes, however, there is a lack of specific design elements to guide the designers to improve the relevant problem points. In order to transform user requirements into specific design elements, the research team used focus group discussions to invite unmanned vending vehicle industry experts, product designers and potential users to conduct in-depth discussions around the core user requirements, and combined with the QFD (Quality Function Deployment) methodology to gradually transform user requirements into specific design elements. In the process of exploration, we found that certain design functions may satisfy multiple user requirements at the same time, and the realization of some requirements requires the synergy of multiple design functions. For this reason, the research team adopts a three-level classification system to refine the core design elements from the three dimensions of functional requirements, user experience, and technical feasibility, in order to ensure the systematic and scientific transformation of requirements, and the relevant design elements and technical requirements are shown in Table 21.

Table 21. Correlation Between User Needs and Elements

Requirement Attributes	Specific needs	Design Elements	Technical Requirements
Must-be Requirements	Route Planning B1	Multimodal Path Optimization Engine D1	BeiDou+UWB fusion positioning technology, dynamic traffic flow prediction model (LSTM), solid-state LiDAR real-time obstacle avoidance algorithm
	Cargo Management B2	Intelligent Dynamic Shelving System D2	RFID spatial topology modeling, temperature control energy consumption optimization algorithm, pressure sensor-based self-balancing mechanism for goods distribution
	Payment System B4	Sensorless Payment Convergence Gateway D4	Multi-biometric aggregation authentication (face + finger vein), zero-trust architecture payment encryption, offline transaction synchronization blockchain
	Operation Convenience B6	Progressive Task Flow Design D6	Operation path entropy analysis model, error operation pattern recognition, context-aware process jump engine
	Commodity display B7	Virtual-reality fusion display system D7	E-ink dynamic labeling, 3D point cloud reconstruction of goods, user rating sentiment analysis model
	Vehicle Stability B10	Active Attitude Control System D10	Six-axis inertial navigation compensation, torque vector allocation algorithm, real-time estimation model of road surface adhesion coefficient.
One-dimensional Requirements	Commodity Selection B3	Semantic Interactive Search System D3	Product knowledge graph construction, natural language intent recognition (BERT), AR spatial projection product localization technology.
	User experience B5	Cognitive load optimization model D5	Eye tracking interaction optimization, personalized recommendation reinforcement learning algorithm, multimodal feedback delay control (<100ms)
	After-sales service support B8	Intelligent Service Routing System D8	Service Demand Prioritization Model, Multi-channel Work Order Auto Assignment, Digital Twin-based Remote Diagnosis Technology
	Emergency Response B11	Edge Computing Emergency Hub D11	Local decision-making redundancy fault-tolerant architecture, intelligent switching of emergency power supply, V2X-based emergency rescue cooperative network
Attractive requirements Requirement Attributes Must-be Requirements	Shape design B12	Parametric Brand Genetic Design D12	Styling semantic analysis toolchain, aerodynamic simulation optimization, rapid prototyping 3D printing process
	Color matching B13	Environmentally Responsive Color System D13	Light color temperature adaptive algorithm, color emotion calculation model, electrochromic polymer material application
	Detailed treatment B14	Micro-interaction Experience Engineering D14	Nanoscale surface tactile treatment, stress distribution simulation for decorative parts, fatigue life prediction model for interior materials

After completing the correlation analysis between user requirements and design elements, it is necessary to further construct a House of Quality (HOQ) model to analyze the relationship and weighting between user requirements and design technical requirements. The core purpose is to comprehensively quantify the importance of user requirements and the correlations between user needs and technical requirements, thereby identifying the key technical directions for the design optimization of unmanned vending vehicles.

First, the comprehensive weights of user requirements obtained through the KANO model and Analytic Hierarchy Process (AHP) are imported as the user-side weights. Subsequently, according to the QFD correlation evaluation criteria, the degree of correlation between user requirements and technical requirements is scored.

Specifically, a strong correlation is assigned a value of 5, a medium correlation a value of 3, a weak correlation a value of 1, and no correlation a value of 0. Based on this, a relationship matrix between user

requirements and technical requirements is established.

The absolute weight of technical requirements is calculated using Equation (20):

$$\omega_j = \sum_{i=1}^n R_{ij} * C_i \quad (20)$$

On this basis, in order to further compare the importance of different technical requirements, this study standardizes the absolute weights and calculates the relative weights of each technical requirement. The calculation formula is shown in Equation (21).

$$H_j = \frac{\omega_j}{\sum_{j=1}^m \omega_j} * 100\% \quad (21)$$

	D1	D2	D3	D4	D5	D6	D7	D8	D10	D11	D12	D13	D14	U
B1	5		1											0.09491
B2		5			2		4						3	0.07323
B3			5		3	2	4						1	0.07252
B4				5	4			1					2	0.12349
B5			3		5	4	2				1		3	0.13175
B6			3		4	5					1		2	0.08580
B7		4	3				5				2	1		0.05662
B8					3			5		1			2	0.05436
B10	3	2							5	1				0.04496
B11	3							1	2	5				0.03670
B12											5	4	3	0.11233
B13							1				3	5	2	0.06321
B14					4	3					2	1	5	0.05022
M	0.7195	0.6826	1.2800	0.6175	2.2239	1.2517	1.1928	0.4320	0.6562	0.4726	1.1825	0.8722	1.9293	
H	0.0532	0.0505	0.0947	0.0457	0.1646	0.0926	0.0883	0.0320	0.0486	0.0350	0.0876	0.0645	0.1428	

Figure 4: QFD Quality House Construction

Based on the above calculation results, the priority ranking of each technical requirement can be further obtained. The results indicate that technical requirements related to user experience received relatively high weights. Among them, the cognitive load optimization model (D5), semantic interaction search system (D3), and micro-interaction experience engineering (D14) all achieved relatively high absolute and relative weights, indicating that users pay greater attention to operational fluency, interaction naturalness, and cognitive efficiency during the shopping process, as shown in Figure 4. In contrast, although some traditional hardware-oriented functions still play a fundamental supporting role, their weights are relatively lower.

These findings suggest that the design focus of unmanned vending vehicles is gradually shifting from merely achieving functional implementation toward optimizing user experience and enhancing intelligent interaction. In other words, users' expectations for intelligent retail devices are no longer limited to "being able to complete a purchase," but are increasingly concerned with "how to complete the shopping process in a more natural, efficient, and cognitively effortless manner."

6. Discussion and Analysis

In terms of relative weight values, the cognitive load optimization model D5, micro-interaction experience engineering D14, and semantic interaction search

system D3 have relatively high weights, reaching 0.1646, 0.1428, and 0.0947, respectively. This indicates that elements related to user experience occupy an important position in the design of unmanned vending vehicles. Users have high expectations and demands for the operation convenience, interaction friendliness and search efficiency of the unmanned vending vehicle. Comparatively speaking, the weights of the intelligent service routing system D8 and the edge computing emergency hub D11 are low, 0.0320 and 0.0350, respectively, indicating that these elements account for a relatively small portion of the current design, probably because their direct impact on user experience is not as significant as the former or they have not yet been given enough attention and development in practical applications.

As consumers' requirements for the shopping experience continue to improve, easy operation, natural interaction, and accurate search have become the key factors to attract users to unmanned vending vehicles [51]. Therefore, during the design process, designers should be more inclined to invest their resources and efforts in those aspects that can directly enhance the user experience in order to fulfill the core needs and expectations of users. As Norman said, "Good design is what makes users feel pleasure and satisfaction when using a product." In the design of unmanned vending vehicles, focusing on user experience-related elements, such as cognitive load optimization model and micro-interaction experience engineering, can effectively enhance user satisfaction and loyalty, thus gaining an advantage in market competition [52]. In the design of unmanned vending vehicles, designers can further study the cognitive characteristics and operating habits of users in depth, and reduce the cognitive load of users by simplifying the interface design, optimizing the operation process, and providing intuitive feedback, so as to make the operation more fluent and natural. For example, adopting progressive guidance design, gradually displaying the functions and operation steps when users use it for the first time, avoiding presenting too much information at one time, reducing the users' memory burden and operation confusion, so that users can gradually familiarize themselves with the operation process and establish the correlation between users and the product. In addition, we pay attention to every micro-interaction between the user and the unmanned vending vehicle, such as button clicking effect, touch feedback, sound prompts, etc., to ensure that the response of these micro-interactions is timely, accurate and in line with the user's expectations. At the same time, the design of micro-interactions can be continuously optimized through user testing and feedback collection to improve the overall user experience and product competitiveness. Focusing on user experience-related elements helps to create

differentiated competitive advantages, attract more users, and increase brand awareness and market share.

The development and maturity of relevant technologies also have a significant influence on the selection and prioritization of design elements. As noted by Matosas-López, technological maturity and reliability are important factors influencing user satisfaction [53]. Therefore, when designing and optimizing unmanned vending vehicles, priority should be given to those elements that are technologically mature and can directly enhance the user experience, such as semantic interactive search systems. Technologies such as semantic interactive search systems have made significant progress in recent years, and their applications are gradually maturing. This makes it easier for designers to integrate them into the design of unmanned vending vehicles, and they can better realize the expected functions, so they are given higher weight in the design. In the specific application process, the application of natural language processing technology should be strengthened to improve the understanding of the user's search intent and the ability to accurately match. By introducing semantic analysis, knowledge graph and other technologies, smarter search recommendation and result presentation can be realized to help users find the required goods faster. In addition, personalized search services can be considered in combination with users' historical purchase records and preferences.

Regarding cargo management, designers should optimize shelf organization according to actual usage requirements and provide appropriate temperature control for hot and cold products. Sibanda et al. developed a high-tech vending machine that integrated security functions with IoT-based temperature regulation, demonstrating the importance of combining operational safety with intelligent cargo management [54]. Product presentation and operational convenience also influence shopping efficiency. Wu et al. found that consumers are more receptive to reviewer recommendations, suggesting that user-rating and review functions may support product selection and improve the shopping experience [55]. Lina et al. further demonstrated that different dimensions of online convenience significantly influence consumers' cognitive and affective attitudes [56]. Accordingly, field observations of user transaction processes can help designers identify operational difficulties and implement targeted improvements.

The scientific contribution of this study lies in the construction of a continuous and traceable user-requirement transformation framework rather than in the separate application of Grounded Theory, the KANO model, AHP, and QFD. By linking qualitative requirement extraction, satisfaction-based classification, expert-supported weighting, and

technical design transformation, the framework establishes a systematic connection between user research and design decision-making. Its applicability is supported by theoretical saturation in the qualitative analysis, 406 valid questionnaire responses, acceptable AHP consistency results, and the successful transformation of 13 user requirement categories into corresponding design elements through the House of Quality. More importantly, the framework is not limited to a specific product form, because requirement identification, priority evaluation, and technical transformation are common tasks in the development of intelligent products. By adjusting the user requirement categories, evaluation criteria, and technical characteristics according to different application contexts, the proposed approach may be extended to smart self-service terminals, mobile retail robots, and other intelligent service systems. Therefore, this study provides both a methodological contribution to user-requirement-driven design research and practical guidance for the development of unmanned vending vehicles and related intelligent products.

7. Conclusions

In this study, a systematic framework for extracting and optimizing the design elements of unmanned vending vehicles was established through the integration of Grounded Theory, the KANO model, AHP, and Quality Function Deployment (QFD). The study focused on transforming user requirements into specific design elements and technical requirements, thereby providing a practical basis for intelligent retail product optimization.

The results indicate that users' demands for unmanned vending vehicles are mainly concentrated in four dimensions: functionality, shopping experience, safety, and design style. Among these dimensions, requirements related to functionality and shopping experience were prominent among the high-priority items on user satisfaction, suggesting that users not only expect stable operational performance but also place increasing emphasis on interaction efficiency, operational convenience, and the overall shopping experience. In addition, safety perception and visual design were also found to influence user trust and product attractiveness.

At the design level, several key elements were identified, including the cognitive load optimization model, semantic interactive search system, intelligent dynamic shelving system, micro-interaction experience engineering, and sensorless payment convergence gateway. The findings suggest that improving interaction fluency and reducing users' cognitive burden are more closely associated with satisfaction improvement than simply increasing functional complexity. This indicates that future unmanned retail systems should pay greater

attention to user behavioral logic and interaction experience in addition to technological performance.

Compared with existing studies that primarily emphasize autonomous navigation, sensing systems, and technical implementation, this study further highlights the importance of user experience factors in intelligent retail environments. The results demonstrate that user-centered design considerations play a critical role in improving product acceptance and enhancing intelligent retail service quality. Furthermore, the identified requirement hierarchy and design priorities provide practical references for optimizing interface systems, operational workflows, and intelligent interaction mechanisms in unmanned vending vehicles.

Although this study established a relatively complete framework for demand extraction and design transformation, several limitations remain. Future research may further expand the sample scope and incorporate users from different regional and consumption backgrounds to improve the generalizability of the findings. In addition, emerging technologies such as adaptive intelligent interaction, augmented reality, and digital twin systems may be further explored to enhance personalized service experiences and dynamic interaction capabilities in intelligent retail environments.

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