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A Kano Model–Driven Requirements Analysis for Intelligent Supervision Platforms in Farmland Abandonment Governance

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Abstract: Accelerated urbanization, sustained rural labor migration, and increasing inefficiencies in land management have contributed to the widespread abandonment of cultivated land in China, thereby posing significant challenges to national food security, agricultural sustainability, and rural revitalization. Although intelligent supervision technologies have been increasingly introduced into agricultural governance systems, the heterogeneous requirements of multiple stakeholders have not been systematically incorporated into existing platform design frameworks. To address this gap, a Kano model–based requirements analysis framework was developed and applied to the governance of farmland abandonment in a major agricultural county in Jiangxi Province, China. A mixed-methods approach integrating literature analysis, semi-structured interviews, and questionnaire surveys was adopted to identify, classify, and prioritize the requirements for an intelligent supervision platform. The identified requirements were categorized into four dimensions: must-be requirements (e.g., policy subsidy information and data stability), one-dimensional requirements (e.g., historical data comparison and land transfer information), attractive requirements (e.g., high-precision monitoring and fallow warning), and indifferent requirements (e.g., user operation training and feedback channels). The findings demonstrated that must-be requirements should be prioritized to ensure the operational reliability of the platform, whereas one-dimensional requirements should be continuously strengthened to improve core capabilities. Attractive requirements were found to significantly enhance user experience and should therefore be gradually integrated. In contrast, indifferent requirements should be strategically managed to avoid unnecessary allocation of resources. Empirical evidence for the optimization of intelligent supervision platforms in farmland abandonment governance was provided by this study, while the applicability of the Kano model in public governance technology requirement analysis was further validated. The findings are expected to contribute to the advancement of intelligent, data-driven, and precision-oriented farmland governance systems in China and other developing agricultural regions.

Keywords: Intelligent supervision platform; Kano model; Farmland abandonment governance; Requirements analysis; Intelligent agricultural governance; Rural land management; China

1 Introduction

Farmland, as a fundamental element of agricultural production, is the core resource for achieving a stable and sufficient food supply [1]. With the acceleration of China's urbanization process, issues such as sustained rural labor migration and the decreasing comparative benefit of land management have become increasingly prominent. This has led to the spread of farmland abandonment from traditional mountainous areas to plain agricultural regions, evolving from sporadic abandonment to contiguous idleness [2]. Between 1992 and 2015, the average annual area of abandoned farmland reached 23,300 km^2, accounting for 18.59% of the total farmland [3]. This trend of non-agriculturalization and non-grain utilization not only weakens the efficiency of land resource utilization but also inflicts a systemic shock on the agricultural production system—when farmland is left idle for an extended period, its physical structure deteriorates, leading to a sharp increase in reclamation costs. The destruction of biodiversity triggers a decline in the ecological service functions of farmland [4, 5], ultimately resulting in a dual predicament of sharply reduced farmland quantity and deteriorated quality [6].

In terms of food security, farmland abandonment directly results in the “hidden loss” of food production capacity, exacerbating the pressure to maintain the red line for farmland [7]. Especially in major grain-producing areas, abandonment may lead to regional imbalances in the food supply chain, weakening the strategic flexibility to respond to international market fluctuations [8]. The United Nations Sustainable Development Goal 2 (SDG 2) emphasizes the importance of eradicating hunger, ensuring food security, improving nutrition, and promoting sustainable agriculture [9]. For the rural economic system, abandoned farmland is not only a waste of idle productive factors but also restricts the development of appropriate scale operations [10]. Land fragmentation hinders the promotion of mechanized operations, and the lack of connectivity between plots reduces investment incentives, creating a vicious cycle of “abandonment–inefficiency–re-abandonment” [2, 11]. This predicament further limits opportunities for farmers to increase their income and delays the process of rural industrial revitalization [6, 8].

In this situation, the innovative intelligent supervision technologies have provided a new pathway to solving the governance dilemma. Satellite remote sensing technology, through multispectral imaging and temporal analysis, could establish a dynamic monitoring network for the utilization status of farmland, accurately identifying the spatial distribution and evolution patterns of abandoned plots [12]. The unmanned aerial vehicle inspection system, with its high-resolution image acquisition capability, can penetrate cloud cover and achieve sub-meter-level interpretation of crop planting conditions. The geographic information system spatial analysis platform, by integrating multiple data sources such as soil moisture content and topography, could construct an early warning model for the risk of farmland abandonment [11]. Compared with the disadvantages of traditional manual inspection, which is time-consuming, labor-intensive, and statistically lagging, this “heaven, earth, and air” collaborative monitoring system could significantly improve the timeliness of problem discovery [13], and its machine learning-supported farming behavior pattern recognition technology makes early intervention and precise policy implementation possible [8, 12]. The widespread application of these intelligent supervision technologies is reshaping the landscape of arable land abandonment governance. They could not only achieve precise monitoring and early warning of abandonment phenomena but also provide a scientific basis for policy formulation [14], greatly improving the efficiency of governance and the precision of resource utilization. Amid the increasingly severe issue of farmland abandonment, the importance of intelligent supervision technologies is becoming more and more prominent.

In recent years, intelligent supervision technologies such as satellite remote sensing, unmanned aerial vehicles, and the geographic information system have been widely applied in the field of dynamic monitoring of agricultural land use. Satellite remote sensing, with its advantage of large-scale continuous observation, provides a stable data source for the identification of abandoned farmland. The extraction accuracy of abandoned boundaries in complex terrains has been significantly improved [6, 15]. Transnational comparative studies have further shown that satellite data presents reliable spatial resolution adaptability in mapping the abandoned agricultural land in Kyzyl-Orda [16] and the transition zone of Europe [17]. To compensate for the lack of micro-scale verification by satellite data, the unmanned aerial vehicle technology has demonstrated unique value in the monitoring of fragmented farmland at high altitudes in the Himalayas through the collaboration of high-resolution image acquisition and ground surveys [18]. Especially in terms of dynamic ecological risk assessment, the time-series aerial data from unmanned aerial vehicles have effectively captured the secondary degradation process of abandoned farmland in the mountainous areas of Nepal [19], and its application in post-processing of irrigated plot classification [20] has further highlighted the technical necessity of collaborative verification from space, earth, and air. The multidimensional analysis capability of the geographic information system technology provides a spatial support framework for abandoned farmland governance decisions. Lithuanian scholars have demonstrated the policy simulation potential of geographical spatial modeling through the evaluation of wind energy development suitability on abandoned land [21], while the research on the impact of terrace abandonment on hydrological processes [22] has confirmed the critical role of multi-source spatiotemporal data fusion in mechanism diagnosis.

Current studies have primarily focused on the performance optimization of single technologies, but in actual governance scenarios, monitoring of farmland abandonment needs to address systematic challenges such as data fragmentation, response delay, and multi-agent collaboration. The intelligent supervision platform builds a “perception–diagnosis–decision” closed-loop system by integrating the large-scale scanning capability of satellite remote sensing, the dynamic supplementary verification mechanism of unmanned aerial vehicles, and the multidimensional spatial analysis function of the geographic information system. This integrated paradigm not only enables the standardized processing of multi-source heterogeneous data, such as the coupled application of remote sensing spectral data and geographic information system-based socioeconomic layers in the analysis of abandonment drivers [23] but also establishes a full-chain response mechanism ranging from anomaly detection to governance feedback. Through the integration of the platform, real-time data transmission, analysis, and sharing can be achieved, improving the efficiency and accuracy of supervision. For example, in the governance of farmland abandonment, the platform is able to quickly locate abandoned areas, analyze their causes, and update the progress of governance in real time.

The construction of existing intelligent supervision platforms often has a technology-oriented tendency, ignoring the actual needs and differences of grassroots governance entities. The management of farmland abandonment involves multiple stakeholders such as government regulators, farmers, and agricultural enterprises, and their needs for platform functions exhibit significant heterogeneity: administrative entities focus on macro-trend judgment and policy simulation; farmers emphasize plot-level early warning feedback; while technical departments value the openness and compatibility of data interfaces. The traditional waterfall development model is difficult to meet the dynamically changing governance needs, and there is an urgent need to introduce systematic requirements analysis methods.

Despite the rapid advancement of intelligent monitoring technologies, three critical research gaps remain unaddressed. First, existing studies have predominantly adopted a technology-driven perspective, focusing on algorithmic improvements and sensor accuracy, while systematically overlooking the heterogeneous needs of end-users such as farmers, grassroots cadres, and government regulators. Second, there is a lack of methodological frameworks capable of prioritizing competing functional requirements under resource constraints, leading to inefficient allocation of development efforts. Third, most platform evaluations have relied on technical performance metrics (e.g., detection accuracy and response time) rather than user satisfaction, resulting in a disconnect between system design and actual governance effectiveness. To address these gaps, this study introduces the Kano model—a requirement analysis tool widely used in marketing and product design—into the public governance domain of farmland abandonment. The novelty of this approach lies in its ability to classify user needs into distinct categories (must-be, one-dimensional, attractive, and indifferent) based on their nonlinear impact on satisfaction, thereby providing a theoretically grounded and empirically actionable prioritization strategy. Specifically, this study contributes by (i) empirically identifying and categorizing 13 requirements for intelligent supervision platforms through a mixed-methods approach in a major agricultural county in Jiangxi Province; (ii) demonstrating how the Better–Worse coefficient analysis overcomes the limitations of traditional frequency-based classification; and (iii) offering a tiered optimization framework that balances essential stability, core functionality, value-added services, and resource efficiency. These contributions provide both theoretical validation of the Kano model's applicability in public governance technology design and practical guidance for platform developers and policymakers.

2 Methodology

2.1 Overview of the Kano Model

In the construction of intelligent supervision platforms for the management of farmland abandonment, accurate requirements identification is essential for achieving efficient governance. Just as enterprises need to prioritize customer needs and preferences and provide high-quality services in pursuit of long-term business success, the development of intelligent supervision platforms also needs to be guided by requirements to enhance user satisfaction and platform application effectiveness. The Kano model, as a classic requirement analysis tool, provides a theoretical framework for this study to deeply analyze the requirements characteristics of intelligent supervision platforms in the management of farmland abandonment and their impact mechanism on satisfaction.

The Kano model was proposed by Japanese scholar Noriaki Kano in 1984, aiming to reveal the nonlinear relationship between product or service functions and user satisfaction through requirement classification [24]. Its core assumption is that different attribute needs contribute significantly differently to user satisfaction. Based on the relationship between customers' satisfaction with product or service features and the degree of requirement fulfillment, the model divides needs into six categories: must-be, performance, attractive, indifferent, reverse, and questionable. Figure 1 shows the characteristic situation of five of these need categories (excluding questionable), that is, the relationship between the degree of possession and user satisfaction [25]. This classification method can help researchers and developers more accurately identify and understand the priority and importance of the requirements.

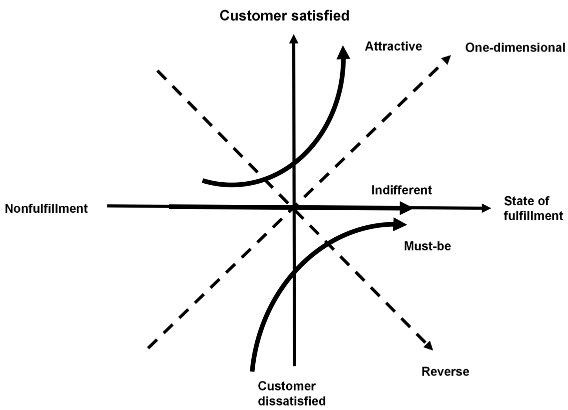

Figure 1. Relationship between feature fulfillment and customer dissatisfaction

(i) Must-be requirements: These are basic functions that users take for granted. Non-fulfillment leads to great dissatisfaction, while fulfillment does not bring additional satisfaction.

(ii) One-dimensional requirements: These are functions that users explicitly expect. Fulfilling these needs brings satisfaction, while unfulfillment leads to dissatisfaction.

(iii) Attractive requirements: These are functions that exceed user expectations. Fulfilling them brings great satisfaction, while non-fulfillment does not lead to dissatisfaction.

(iv) Indifferent requirements: These functions have no significant impact on user satisfaction. Whether they exist or not, users do not have obvious satisfaction or dissatisfaction.

(v) Reverse requirements: These are functions that some users consider unnecessary or even harmful. Fulfilling these needs may lead to dissatisfaction instead.

(vi) Questionable requirements: These are needs for which users give contradictory answers in surveys and usually require further investigation and confirmation.

2.2 Application of the Kano Model in Research

When applying the Kano model in research, the following general steps are typically followed:

Step 1. Identification and classification of needs. Potential needs are extensively collected through literature reviews, interviews, focus group discussions, or brainstorming sessions to provide a basis for Kano questionnaire design.

Step 2. Questionnaire design. The Kano questionnaire is designed based on the identified needs. Each need in the questionnaire includes two questions: a functional question ("How would you feel if the platform had this function?") and a reverse question ("How would you feel if the platform did not have this function?"). The needs are classified into the above-mentioned six types according to the users' answers. For questionable needs, further verification is carried out through interviews or expert evaluations.

Step 3. Data collection. Appropriate research subjects, such as users, customers, stakeholders, etc., are selected to ensure the representativeness of the sample. The feedback is collected extensively through both online and offline methods. Online, large-scale data collection is conducted through survey platforms, while offline, deeper information is obtained through interviews and workshops. During the data collection stage, attention should be paid to the diversity of the sample and the integrity of the data to ensure the validity of subsequent analysis results.

Step 4. Data analysis. Statistical analysis is performed on the collected questionnaire data to determine the classification and priority of various needs. In the traditional application process of the Kano model, based on survey results and the frequency analysis, there are currently two main common and widely used methods to classify the needs. The first method follows the traditional Kano need classification method and classifies needs based on the two-dimensional attribute classification table of the Kano model. It calculates the statistical frequency of each need attribute in different Kano categories and uses the category corresponding to the maximum frequency as the basis for classifying the need. However, this method completely ignores the frequency of other need attributes, which may lead to the loss of a large amount of statistical data information and thus affect the accuracy and scientific validity of the classification results [26].

The Kano model is particularly suitable for analyzing requirements in public governance platforms such as intelligent farmland supervision systems for three reasons. First, unlike commercial products where user satisfaction directly correlates with purchase behavior, governance platforms serve multiple stakeholders (farmers, local officials, and policymakers) with often conflicting priorities. The Kano model's nonlinear categorization capability helps identify which requirements are non-negotiable (must-be) versus those that can be phased in based on resource availability. Second, public sector technology projects frequently suffer from "feature creep"—the addition of technically impressive but low-impact functionalities driven by vendor interests rather than user needs. The Kano model's Better–Worse coefficient provides an objective, data-driven basis for prioritizing requirements, thereby mitigating resource misallocation. Third, the model's distinction between explicit expectations (one-dimensional) and latent needs (attractive) is especially valuable in governance contexts where end-users—particularly smallholder farmers—may lack the technical vocabulary to articulate aspirational functionalities. By systematically capturing both stated and unstated needs, the Kano model bridges the communication gap between technologists and grassroots users, ensuring that platform development aligns with real-world governance priorities rather than abstract technical benchmarks.

Therefore, Berger improved the Kano model in 1993 by introducing the Better–Worse coefficient [27]. That is the second classification method, called the Better–Worse coefficient classification method. The Better coefficient, also known as the satisfaction index, is calculated through a specific formula and is used to measure the degree to which the satisfaction of customers is improved when a service need is met. Its calculation formula is shown in Eq. (1); the Worse coefficient, also known as the dissatisfaction index, is also calculated through a specific formula and is used to measure the impact on customer dissatisfaction when a service need is eliminated. Its calculation formula is shown in Eq. (2). In the actual application of this classification method, the needs are initially classified based on the two-dimensional attribute classification table of the Kano model and the statistical frequency of each need attribute in different Kano categories is calculated. Then, Eq. (1) and Eq. (2) are used to calculate the satisfaction and dissatisfaction index values of each need, respectively. Finally, the type of attribute is determined according to the following classification criteria: when the satisfaction index value is less than 0.5 and the absolute value of the dissatisfaction index value is greater than 0.5, it is a must-be need; when the satisfaction index value is greater than 0.5 and the absolute value of the dissatisfaction index value is greater than 0.5, it is a one-dimensional need; when the satisfaction index value is greater than 0.5 and the absolute value of the dissatisfaction index value is less than 0.5, it is an attractive need; when the satisfaction index value is less than 0.5 and the absolute value of the dissatisfaction index value is less than 0.5, it is an indifferent need. The two-dimensional attribute classification of the Kano model is presented in Table 1 [28].

Table 1. Two-dimensional attribute classification of the Kano model

Positive Question	Negative Question				
	Dislike	**Tolerate**	**Neutral**	**Expect**	**Like**
Dislike	Q	R	R	R	R
Tolerate	M	I	I	I	R
Neutral	M	I	I	I	R
Expect	M	I	I	I	R
Like	O	A	A	A	Q

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

$$SI = \frac{F(A) + F(O)}{F(A) + F(O) + F(M) + F(I)} \tag{1}$$

$$DSI = \frac{F(M) + F(O)}{F(A) + F(O) + F(M) + F(I)} * (-1) \tag{2}$$

where, $F(A), F(O), F(M)$, and $F(I)$ represent the frequency of attractive attributes, one-dimensional attributes, must-be attributes, and indifferent attributes, respectively.

3 Case Study

The intelligent supervision platform from a major agricultural county in Jiangxi Province was selected as a case study for in-depth research. This region is a typical major agricultural county. In recent years, with the acceleration of urbanization, the outflow of the rural labor force has become serious, and the problem of cultivated farmland abandonment has become increasingly prominent, which has become an important challenge for local sustainable agricultural development. In response to this issue, the local government has introduced intelligent supervision technologies and established an intelligent supervision platform integrating satellite remote sensing, drone inspection, and the geographic information system, aiming to enhance the efficiency and precision of cultivated farmland abandonment management through modern technological means. However, despite the continuous increase in technological investment, the actual application effect of the platform is still restricted by multiple factors, especially in meeting the needs of different stakeholders. Therefore, this study selected this platform as a case study and conducted an in-depth analysis of its actual operation performance through field research, in-depth interviews, and data analysis. After identifying the existing problems and combining with the analysis results of the Kano model, targeted improvement suggestions were proposed to provide reference for the construction and optimization of intelligent supervision platforms in similar regions.

3.1 Identification and Classification of the Requirements for the Intelligent Supervision Platform

3.1.1 Preliminary extraction of the requirements for the intelligent supervision platform

A multi-channel requirement identification method was adopted to obtain the potential requirement indicators of the intelligent supervision platform. On the one hand, by utilizing the scientific literature database search technology, relevant literature was retrieved from mainstream academic literature databases, including the Web of Science and Engineering Index databases [1, 2, 5, 10–14]. This study focuses on the application of intelligent supervision platforms in similar agricultural governance scenarios, requirement analysis, and user feedback. The literature covers multiple fields, including smart agriculture, remote sensing technology, geographic information systems, and unmanned aerial vehicle applications, providing theoretical support and technical reference for identifying potential requirements.

On the other hand, through the actual investigation of the intelligent supervision platform in a major agricultural county in Jiangxi Province, in-depth interviews were conducted. The interviewees included seven local farmers who were directly involved in agricultural production and were the end users of the intelligent supervision platform; four agricultural business entities, including family farm owners, large-scale planting households, and agricultural cooperative leaders, whose requirements for the platform mainly focused on production management and economic benefit improvement; three grassroots cadres such as village cadres and township agricultural technicians, who paid attention to how the platform could assist grassroots governance and agricultural services; and three staff members from government departments such as the Agriculture and Rural Affairs Bureau and the Natural Resources Bureau, who put more emphasis on the macro decision-making support and policy implementation assistance of the platform. Through the feedback from these interviewees, combined with the results of the literature review, 17 requirements were initially extracted and divided into three dimensions, as shown in Table 2.

Table 2. Preliminary requirements of the intelligent supervision platform

Dimension	Requirement	Content Description	Source
Functional requirements	High-precision monitoring	Real-time monitoring of farmland utilization and identification of abandoned land	[1, 10, 12, 13]
	Farmland abandonment alert	Timely issuance of early warning information regarding farmland abandonment	[5, 12, 14]
	Historical data comparison	Provision of historical data comparison functions to analyze the trend of abandonment	[1, 2, 10, 13, 14]
	Land transfer information	Provision of land transfer requirements and resource information	[1, 2, 5, 14]
	Land transfer transaction support	Provision of online land transfer transaction functions	[2, 5, 11]
	Policy subsidy information	Accurate dissemination of information related to grain planting subsidies and reclamation policies	[1, 10, 12, 13]
	Planting technical guidance	Provision of guidance on plant cultivation techniques and pest and disease control	Interview
	Agricultural meteorological service	Provision of meteorological warnings and agricultural activity suggestions	Interview
Service requirements	User operation training	Provision of platform operation training and technical support	Interview
	Online customer service and consultation	Provision of online customer service and technical consultation	Interview
	User feedback channels	Provision of channels for user feedback and suggestions	Interview
	User community or forum	Provision of a community or forum for user communication	Interview
Experience requirements	Interface simplicity	A concise and user-friendly interface that is easy to operate	Interview
	Multi-terminal adaptation	Support for multiple terminals such as mobile phones, tablets, and computers	Interview
	Data stability	Stable platform operation without data loss or errors	[5, 10, 11]
	User customization options	Support for customization of functions and information notifications according to user needs	Interview
	Platform background music	Provision of background music functions to enhance user experience	Interview

3.1.2 Requirement filtering for the intelligent supervision platform

After initially identifying the requirements of the intelligent supervision platform, in order to further improve the reasonableness, scientific validity, and credibility of the requirement indicators, a questionnaire survey was conducted among the platform users in the major agricultural county. The questionnaire adopted a five-point Likert scale, with scores ranging from 1 to 5, representing "not important," "generally important," "important," "more important," and "very important," respectively. The survey was designed to systematically assess the importance that users attached to various needs of the intelligent supervision platform. Through the questionnaire survey, 120 valid questionnaires were collected. The analysis of the questionnaire survey results was centered on quantitative evaluation. By calculating the arithmetic mean of each requirement and the requirement support rate (a score of 4 and above), a scientific basis was provided for determining the priority of needs. Taking the first requirement, "high-precision monitoring," as an example, the scoring calculation process is presented in Table 3.

Table 3. Score distribution for "High-Precision Monitoring"

Score	1	2	3	4	5
Frequency	0	3	7	20	90

The formula for calculating the arithmetic mean is shown in Eq. (3):

$$\overline{X_i} = \frac{1}{N}\sum_{j=1}^{N} X_{ij} \tag{3}$$

where, $\bar{X}_i$ represents the arithmetic mean of requirement i, N is the total number of samples (120 in this study), and X_{ij} is the score given by respondent j for requirement i.

By substituting the score distribution data into Eq. (3), the following expression can be obtained:

$$\overline{X_1} = \frac{(90\times 5)+(20\times 4)+(7\times 3)+(3\times 2)+(0\times 1)}{120} = 4.64$$

The formula for calculating the support rate is shown in Eq. (4):

$$\text{Support rate}_i = \frac{\text{Count}(X_{ij}\geq 4)}{N}\times 100\% \tag{4}$$

where, $\text{Count}(X_{ij}\geq 4)$ represents the number of respondents who assigned a score of 4 or higher to requirement i.

By substituting the score distribution data into Eq. (4), the following expression can be obtained:

$$\text{Support rate}_1 = \frac{90+20}{120}\times 100\% = 91.7\%$$

To ensure the scientificity and representativeness of the requirements, elimination criteria were established. If a requirement met both of the following conditions simultaneously, that requirement was eliminated, as shown in Eq. (5):

$$\begin{cases} \overline{X_i} < 3.5 \\ \text{Support rate }_j < 55\% \end{cases} \tag{5}$$

The results show that the arithmetic mean of the "high-precision monitoring" requirement is 4.64, and the support rate is 91.7%, indicating that users attach great importance to this requirement. Following the above process, a similar quantitative analysis was conducted for the other 16 requirements and the priority of each requirement was ultimately determined, as shown in Table 4.

By analyzing the above data, it was found that in terms of functional requirements, two requirement indicators, "planting technical guidance" and "agricultural meteorological services," were eliminated. In terms of service requirements, the requirement indicator of "user community or forum" was eliminated. In terms of experience requirements, the requirement indicator of "platform background music" was eliminated.

After the above process, 13 requirement indicators of the intelligent supervision platform were finally determined and divided into three dimensions: functional requirements, service requirements and experience requirements, as shown in Table 5 and Figure 2.

Table 4. Distribution of requirement scores and quantitative analysis results

Requirement	1	2	3	4	5	Average Score	Support Rate (%)
High-precision monitoring	0	3	7	20	90	4.64	91.7
Farmland abandonment alert	0	2	5	18	95	4.73	94.2
Historical data comparison	0	1	5	15	99	4.78	95.0
Land transfer information	2	5	10	35	68	4.40	85.8
Land transfer transaction support	8	12	25	40	35	3.92	62.5
Policy subsidy information	1	4	8	30	77	4.53	89.2
Planting technical guidance	35	30	25	20	10	2.96	25.0
Agricultural meteorological service	12	18	30	35	25	3.46	50.0
User operation training	10	15	25	45	25	3.67	58.3
Online customer service and consultation	3	7	12	38	60	4.60	81.7
User feedback channels	5	10	20	45	40	3.96	70.8
User community or forum	18	25	40	25	12	3.08	30.8
Interface simplicity	8	12	25	40	35	3.83	62.5
Multi-terminal adaptation	10	15	25	45	25	3.67	58.3
Data stability	5	10	20	45	40	3.96	70.8
User customization options	3	7	12	38	60	4.28	81.7
Platform background music	45	30	25	15	5	2.71	16.7

Table 5. Kano-based requirements of the intelligent supervision platform for farmland abandonment management

Dimension	Requirement	Content Description
Functional requirements	High-precision monitoring	Real-time monitoring of farmland utilization and identification of abandoned land
	Farmland abandonment alert	Timely issuance of early warning information regarding farmland abandonment
	Historical data comparison	Provision of historical data comparison functions to analyze the trend of abandonment
	Land transfer information	Provision of land transfer requirements and resource information
	Land transfer transaction support	Provision of online land transfer transaction functions
	Policy subsidy information	Accurate dissemination of information related to grain planting subsidies and reclamation policies
Service requirements	User operation training	Provision of platform operation training and technical support
	Online customer service and consultation	Provision of online customer service and technical consultation
	User feedback channels	Provision of channels for user feedback and suggestions
Experience requirements	Interface simplicity	A concise and user-friendly interface that is easy to operate
	Multi-terminal adaptation	Support for multiple terminals such as mobile phones, tablets, and computers
	Data stability	Stable platform operation without data loss or errors
	User customization options	Support for customization of functions and information notifications according to user needs

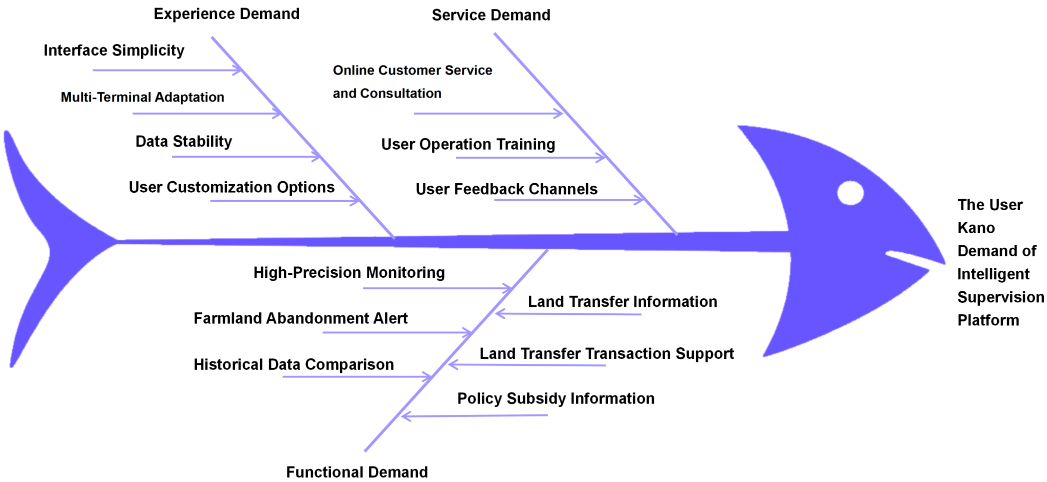

Figure 2. Kano-based requirements of the intelligent supervision platform

3.2 Design of the Kano Questionnaire

3.2.1 Questionnaire content design

The Kano questionnaire was designed based on the Kano-based requirements summarized in Table 5. The questionnaire consisted of two parts: personal basic information of respondents and requirement-related questions regarding the intelligent supervision platform, as shown in Table 6.

Table 6. Kano questionnaire for requirements of the intelligent supervision platform

Category	Items	Question Number(s)
Personal information	Identity, age, gender, years of using the intelligent supervision platform, familiarity with the intelligent supervision platform	1–5
Functional requirement	High-precision monitoring, farmland abandonment alert, historical data comparison, land transfer information, land transfer transaction support, policy subsidy information	6–11
Service requirement	User operation training, online customer service and consultation, user feedback channels	12–14
Experience requirement	Interface simplicity, multi-terminal adaptation, data stability, user customization options	15–18

3.2.2 Design of questionnaire response method

The Kano questionnaire was designed by evaluating each requirement of the intelligent supervision platform from two aspects: the positive aspect (the user's feeling when the platform provides a certain requirement function) and the negative aspect (the user's feeling when the platform does not provide a certain requirement function). Users were asked to choose their true feelings from five options: "dislike," "tolerate," "neutral," "expect," and "like." These five emotional levels were assigned values of 1, 2, 3, 4, and 5, respectively. Table 7 presents one sample item from the Kano questionnaire, taking "Farmland Abandonment Alert" as an example.

Table 7. Example of the Kano questionnaire

Question	Dislike	Tolerate	Neutral	Expect	Like
If the platform provides this function	1	2	3	4	5
If the platform does not provide this function	1	2	3	4	5

Note: "Farmland Abandonment Alert" refers to the timely issuance of early-warning information regarding farmland abandonment.

3.3 Data Collection

This questionnaire survey was conducted through a combination of online and offline methods. As for the online means, the questionnaire was mainly distributed through the Questionnaire Star platform, and the dissemination range was expanded through WeChat, e-mail and other channels. As for the offline means, paper questionnaires were distributed directly to members of local agricultural communities, village committees and other places. In total, 343 questionnaires were distributed, including 195 online questionnaires and 148 offline questionnaires. With 257 questionnaires being finally collected, the response rate was about 74.9%. The questionnaires with incomplete filling or obvious logical errors were eliminated, resulting in 204 valid questionnaires, with an effective rate of about 79.4%. These 204 valid questionnaires covered all four stakeholder groups involved in local farmland abandonment governance. Specifically, the sample comprised 78 ordinary smallholder farmers (38.2%), who were the primary end-users of the platform and directly affected by abandonment governance decisions; 52 agricultural business entities (25.5%), including family farm owners, large-scale planting households, and cooperative leaders, whose operations depended on land consolidation and timely abandonment alerts; 41 grassroots cadres and agricultural technicians (20.1%), who were responsible for on-ground verification, farmer training, and local policy implementation; and 33 staff members from government departments (16.2%) such as the Agriculture and Rural Affairs Bureau and the Natural Resources Bureau, who utilized the platform for macro-level decision-making and policy simulation.

This distribution closely mirrors the actual stakeholder composition in the study area (a major agricultural county in Jiangxi Province), where smallholder farmers constitute approximately 40–45% of agricultural decision-makers, business entities represent 25–30%, and government/technical personnel comprise the remainder. Furthermore, the sample achieved gender balance (52% male, 48% female) and captured a range of ages (25–65 years) and digital literacy levels (from farmers with limited smartphone experience to technical specialists with geographic information system training). To ensure representativeness, stratified purposive sampling was employed, intentionally recruiting participants from three distinct geographical zones within the county (northern, central, and southern) to account for variations in land quality, abandonment severity, and access to digital infrastructure. This sampling strategy, combined with the 79.4% effective response rate and high reliability scores (Cronbach's $\alpha > 0.81$), provides confidence that the collected data adequately represent the diversity of stakeholder perspectives in typical Chinese agricultural counties facing farmland abandonment challenges.

3.3.1 Analysis of reliability

Reliability, also known as consistency, refers to the consistency and stability of the results when the measurement tool is repeatedly measured. In this case, Cronbach's α coefficient was used to evaluate the reliability quality of the questionnaire. The higher the α value, the better the internal consistency of the measurement tool. It is generally believed that an α value greater than 0.7 indicates good reliability, and the closer it is to 1, the higher the reliability quality.

SPSS 27 software was used to conduct reliability tests on the positive and negative questions of the questionnaire, respectively. The results are shown in Table 8. The Cronbach's α coefficients of both the positive and negative questions of the Kano questionnaire are above 0.8, indicating that the reliability quality of the questionnaire is very high. The test results of the questionnaire are quite reliable, showing good consistency and stability.

Table 8. Analysis of reliability for the Kano questionnaire

Question Type	Number of Items	Sample Size	Cronbach's α Coefficient
Positive questions	13	204	0.811
Negative questions	13	204	0.816

3.3.2 Analysis of validity

Validity refers to whether the measurement tool can accurately measure what it is intended to measure, i.e., whether the questions designed in the questionnaire are reasonable. Factor analysis was used in the study for validity analysis. The suitability of the data for factor analysis was assessed using the Kaiser–Meyer–Olkin (KMO) measure and Bartlett's test of sphericity. The KMO statistic compares the simple correlation coefficients between variables and partial correlation coefficients, with a range between 0 and 1. Generally, the KMO value should be at least greater than 0.5, preferably above 0.7. Bartlett's test of sphericity is used to test the degree of correlation between variables. If the generated p-value is below the significance level of 0.05, it indicates that the null hypothesis is rejected, and it is considered that the variables are suitable for factor analysis.

SPSS 27 software was used to conduct validity tests on the positive and negative questions of the questionnaire, respectively. As shown in Table 9, the KMO values of both the positive and negative questions are greater than 0.5, and the p-values of Bartlett's test of sphericity are both less than 0.001, which is below the critical value of the significance level of 0.05. This indicates that the questionnaire for investigating the requirements of the intelligent supervision platform has good validity.

Table 9. Validity test results of the Kano questionnaire

Question Type	Kaiser–Meyer–Olkin	Bartlett's Test of Sphericity	
		Approximate Chi-Square	p-value
Positive questions	0.701	1119.458	<0.001
Negative questions	0.643	1076.419	<0.001

3.4 Classification of the Requirements for the Intelligent Supervision Platform in Farmland Abandonment Management

3.4.1 Two-dimensional classification

In this case, SPSS software was used to perform statistical analysis on the questionnaire data regarding the requirements of the intelligent supervision platform. The classification of the requirements was based on the two-dimensional attribute classification of the Kano model (Table 1). The statistical frequency of each requirement attribute in different Kano categories was calculated, and the category corresponding to the maximum frequency value was used as the basis for classifying the functional requirements. Finally, all requirements were classified according to this method, and their respective Kano requirement categories were determined. The attribute classification of the requirements for the intelligent supervision platform is shown in Table 10. Then, Table 10 was summarized to obtain the two-dimensional attribute classification statistics of the requirements for the intelligent supervision platform, as shown in Table 11.

Table 10. Classification of the requirements for the intelligent supervision platform

No.	Requirement	Attractive (A)	One-Dimensional (O)	Must-be (M)	Indifferent (I)	Reverse (R)	Result
K1	High-precision monitoring	68	51	6	79	0	I
K2	Farmland abandonment alert	43	62	27	72	0	I
K3	Historical data comparison	45	85	31	43	0	O
K4	Land transfer information	26	103	40	35	0	O
K5	Land transfer transaction support	30	96	28	50	3	O
K6	Policy subsidy information	26	60	58	60	0	O
K7	User operation training	50	50	14	90	0	I
K8	Online customer service and consultation	10	90	58	46	0	O
K9	User feedback channels	22	49	40	90	3	I
K10	Interface simplicity	52	40	1	108	0	I
K11	Multi-terminal adaptation	12	56	45	91	0	I
K12	Data stability	25	71	43	65	0	O
K13	User customization options	50	45	34	75	0	I

Table 11. Two-dimensional classification statistics of the requirements for the intelligent supervision platform

Classification Result	Number	Serial Number(s)
Attractive (A)	0	None
One-dimensional (O)	6	K3, K4, K5, K6, K8, K12
Indifferent (I)	7	K1, K2, K7, K9, K10, K11, K13
Must-be (M)	0	None
Reverse (R)	0	None

Table 10 and Table 11 show the classification results of the requirements for the intelligent supervision platform. The six one-dimensional requirements include K3 (historical data comparison), K4 (land transfer information), K5 (land transfer transaction support), K6 (policy subsidy information), K8 (online customer service and consultation), and K12 (data stability). The seven indifferent requirements include K1 (high-precision monitoring), K2 (farmland abandonment alert), K7 (user operation training), K9 (user feedback channels), K10 (interface simplicity), K11 (multi-terminal adaptation) and K13 (user customization options). However, there are no attractive or must-be requirements. This result stems primarily from a limitation of the traditional Kano model. When classifying requirements, the traditional Kano model applies the maximum frequency principle—assigning each requirement to the category with the highest response count while ignoring the distribution across other categories. For example, for the requirement K2 (farmland abandonment alert), the one-dimensional statistical frequency is 62, while the indifferent statistical frequency is 72, and the frequencies of the two categories are very close. If the requirement is classified as indifferent based on the principle of maximum frequency, the classification result may lack rigor and scientificity. Therefore, in order to further improve the accuracy of requirement attribute classification, it is necessary to conduct a Better–Worse coefficient analysis on the statistical frequencies of two-dimensional attribute classifications.

3.4.2 Better–Worse coefficient classification

By substituting the data in Table 10 into the Better–Worse coefficient calculation formula, the Better value, Worse value, and classification result for the requirements of the intelligent supervision platform were obtained, as shown in Table 12.

Based on the Better–Worse coefficient values of the requirements of the intelligent supervision platform in Table 12, a Better–Worse four-quadrant scatter diagram was constructed by utilizing the Better value as the x-coordinate and the absolute value of the Worse value as the y-coordinate. The origin of the coordinate axis was set at (0.5, 0.5), as shown in Figure 3.

Table 12. Better–Worse coefficient values of the requirements for the intelligent supervision platform

No.	Requirement	Better	Worse	Result
K1	High-precision monitoring	0.583	-0.279	Attractive (A)
K2	Farmland abandonment alert	0.515	-0.436	Attractive (A)
K3	Historical data comparison	0.637	-0.569	One-dimensional (O)
K4	Land transfer information	0.632	-0.701	One-dimensional (O)
K5	Land transfer transaction support	0.618	-0.608	One-dimensional (O)
K6	Policy subsidy information	0.422	-0.578	Must-be (M)
K7	User operation training	0.490	-0.314	Indifferent (I)
K8	Online customer service and consultation	0.490	-0.725	Must-be (M)
K9	User feedback channels	0.353	-0.443	Indifferent (I)
K10	Interface simplicity	0.458	-0.204	Indifferent (I)
K11	Multi-terminal adaptation	0.333	-0.495	Indifferent (I)
K12	Data stability	0.471	-0.559	Must-be (M)
K13	User customization options	0.466	-0.387	Indifferent (I)

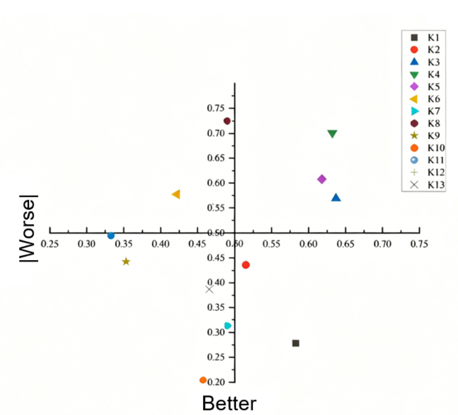

Figure 3. Better–Worse four-quadrant scatter diagram

4 Results and Discussion

4.1 Analysis of the Better–Worse Coefficient Classification Results

In Figure 3, requirements in the first quadrant (Better > 0.5, |Worse| > 0.5) are classified as one-dimensional—their fulfillment proportionally increases user satisfaction, while their absence causes proportional dissatisfaction. In this study, three requirements exhibit this pattern: K3 (historical data comparison), K4 (land transfer information), and K5 (land transfer transaction support). The governance implication of this finding is significant because these functions directly address the core economic drivers of abandonment. Historical data comparison (K3, Better = 0.637, Worse = -0.569) allows users to track abandonment trends over time, enabling evidence-based assessment of policy effectiveness. Land transfer information (K4, Better = 0.632, Worse = -0.701) and transaction support (K5, Better = 0.618, Worse = -0.608) tackle the root cause of abandonment—land fragmentation and lack of access to rental markets. Unlike basic stability requirements (which merely prevent dissatisfaction), these functions actively generate satisfaction by offering practical solutions to farmers' land disposal problems. For platform designers, this implies that investments in K3–K5 yield directly observable returns in user engagement and perceived utility. Importantly, the high Worse coefficients for K4 and K5 (-0.701 and -0.608, respectively) indicate that users are particularly sensitive to the absence of land transfer functionalities, reflecting the urgent local requirement for land consolidation mechanisms amidst labor outmigration.

Requirements in the second quadrant (Better < 0.5, |Worse| > 0.5) are classified as must-be: their absence sharply reduces satisfaction, but their presence does not increase satisfaction beyond a neutral baseline. Three requirements belong to this category: K6 (policy subsidy information), K8 (online customer service and consultation), and K12 (data stability). The classification of these functions as must-be reveals an important asymmetry in user expectations. For data stability (K12, Better = 0.471, Worse = -0.559), users treat error-free operation as a non-negotiable entitlement. Any data loss or system crash would immediately erode trust, yet simply providing stable operation earns no credit—users consider that it is the platform's baseline duty. Similarly, policy subsidy information (K6, Better = 0.422, Worse = -0.578) is expected as a standard service, likely because users can obtain such information through other channels (e.g., village announcements and government offices). Its presence on the platform does not delight, but its absence would be perceived as a serious omission. The governance lesson is twofold. First, must-be requirements must be fully implemented before any other category; launching a platform with incomplete basic services risks irreversible user rejection. Second, developers should avoid over-investing in must-be features beyond adequacy, as additional improvements yield diminishing returns in satisfaction. For K8 (online customer service, Better = 0.490, Worse = -0.725), the exceptionally high Worse coefficient (-0.725, the highest in absolute value among all requirements) indicates that users are extremely intolerant of poor technical support. This suggests that while the platform does not need sophisticated artificial intelligence chatbots initially, it must guarantee a responsive human support channel—a low-cost but high-impact must-be function.

Requirements in the third quadrant (Better < 0.5, |Worse| < 0.5) are classified as indifferent—their presence or absence has no statistically significant impact on user satisfaction. Five requirements fall into this category: K7 (user operation training), K9 (user feedback channels), K10 (interface simplicity), K11 (multi-terminal adaptation), and K13 (user customization options). The indifferent classification does not mean these functions are useless, but rather that users do not perceive them as critical differentiators. For example, interface simplicity (K10, Better = 0.458, Worse = -0.204) and multi-terminal adaptation (K11, Better = 0.333, Worse = -0.495) are features that platform developers often assume are highly valued. However, the data of this study show that they have minimal impact on satisfaction. One possible explanation is that the current user base—including smallholder farmers with limited digital experience—prioritizes access to accurate abandonment information over aesthetic or convenience factors. As one interviewed farmer stated, "I don't care how the platform looks; I just want to know which of my plots are at risk." The governance implication is one of resource allocation efficiency. Indifferent requirements should receive the lowest development priority. However, complete neglect may be shortsighted, as some indifferent features (e.g., user feedback channels, K9) could become more important as the platform matures and user expectations evolve. Therefore, this study recommends minimal viable implementation for K7–K13—basic versions that meet minimal functional standards without costly embellishments—and periodic re-evaluation of their classification as user experience grows.

The fourth quadrant contains attractive requirements (Better > 0.5, |Worse| < 0.5), whose presence delights users but whose absence does not cause dissatisfaction. Two technologically sophisticated functions fall into this category: high-precision monitoring (K1, Better = 0.583, Worse = -0.279) and farmland abandonment alert (K2, Better = 0.515, Worse = -0.436).

The governance interpretation is particularly nuanced. While these functions represent the cutting edge of remote sensing and early warning capabilities, users do not expect them as basic entitlements—likely due to the prevailing technology-oriented platform design that has historically prioritized backend performance over user-facing intelligence. Consequently, implementing K1 and K2 generates substantial satisfaction gains (Better coefficients > 0.5) because they exceed baseline expectations, offering value-added services such as sub-meter-level abandoned plot identification and predictive risk alerts. However, their absence does not reduce satisfaction (|Worse| < 0.5) because users have not yet internalized these as standard features. This classification provides strategic guidance: rather than delaying platform launch until all advanced features are ready, developers should first ensure must-be and one-dimensional needs are met (ensuring basic usability) and then progressively introduce attractive qualities in phases. For instance, deploying basic abandonment detection followed by a second-phase upgrade with precision monitoring and predictive alerts allows continuous user satisfaction improvement without overwhelming technical teams or inflating initial budgets. In the context of farmland governance, attractive requirements can serve as key differentiators when competing with alternative monitoring approaches (e.g., manual inspection), helping to drive platform adoption among initially skeptical users.

4.2 Recommendations for the Intelligent Supervision Platform in Farmland Abandonment Management

4.2.1 Optimization of must-be requirements to strengthen the operational foundation of the platform

The first function optimization of the intelligent supervision platform should focus on the must-be requirements to ensure the stability and reliability of its basic functions. Data stability is one of the most fundamental requirements that users have for the platform; therefore, the platform should strengthen its technological infrastructure, adopt highly reliable servers and data backup mechanisms, and ensure the continuous availability and integrity of data. At the same time, a professional operation and maintenance team should be established to conduct regular maintenance and upgrades of the platform and promptly address potential issues. Additionally, a dedicated user feedback channel should be set up to quickly respond to users' feedback on data stability, further enhancing their trust in the platform. Policy subsidy information dissemination is also one of the essential needs. The platform should strengthen cooperation with government departments to obtain and disseminate the latest information on grain cultivation subsidies and reclamation policies in time, while also providing a policy interpretation feature to help users better understand and apply these policies. The online customer service and consultation function is an important guarantee for the platform to provide technical support and services. A professional customer service team should be established to offer timely and efficient technical support and consulting services. The customer service system should be optimized by adding intelligent customer service functions to quickly respond to common questions, while ensuring that human customer service can promptly intervene to handle complex issues. By meeting these essential needs, the platform can build basic trust with users and lay a solid foundation for the subsequent optimization and expansion of functions.

4.2.2 Enhancement of one-dimensional requirements to improve core platform performance

One-dimensional requirements exhibit significant positive and negative effects on user satisfaction. Therefore, the platform should focus on optimizing these requirements. The historical data comparison function is crucial for users to understand the trends and patterns of land abandonment. The platform should provide more comprehensive and convenient historical data comparison tools, adding visualization charts and trend analysis functions, to help users intuitively understand the trends of land abandonment and formulate more effective governance strategies. The land transfer information dissemination function is of great significance for promoting the optimal allocation of land resources. The platform should optimize the dissemination mechanism, introduce intelligent recommendation algorithms, and accurately disseminate land transfer information that meets users' needs. In collaboration with the land transfer market and relevant departments, it ensures the timeliness and accuracy of the information. The land transfer transaction support function provides convenience for users to conduct online land transfer transactions. The platform should simplify the transaction process and offer online transaction support functions, including electronic contract signing and fund escrow services, to ensure the safety and convenience of transactions. By optimizing one-dimensional requirements, the platform can significantly enhance user satisfaction and strengthen users' reliance on and recognition of the platform.

4.2.3 Optimization of attractive requirements to enhance value-added platform services

Attractive requirements can provide users with additional value and convenience, significantly enhancing user satisfaction. The high-precision monitoring function is one of the core functions of the intelligent supervision platform. The platform should improve the accuracy of satellite remote sensing and drone technology, optimize the identification algorithm of abandoned land, and combine it with the geographic information system technology to achieve dynamic monitoring and real-time warning. It should also add functions for analyzing and interpreting monitoring data to provide users with a deeper analysis of cultivated land utilization. The farmland abandonment alert can promptly send early warning information on abandoned land to users, helping them take measures in advance to avoid further deterioration of land abandonment issues. The platform should integrate multi-source data (such as meteorological data and land use data) to predict abandonment risks in advance, send timely warning information to users, and provide grading and classification functions for warning information, helping users take corresponding measures according to the level of risk. By gradually improving these attractive requirement functions, the platform can provide value-added services for users, enhancing the platform's competitiveness and user experience.

4.2.4 Optimization of indifferent requirements to avoid resource misallocation

Indifferent requirements have a relatively minor impact on user satisfaction, but the platform still needs to plan reasonably to avoid resource misallocation. The user operation training is really important to help users better grasp the usage of the platform. The platform should provide multiple training methods, such as online tutorials, video demonstrations, and operation manuals, and regularly update and optimize the training content according to user feedback to ensure its practicality and comprehensibility. The user feedback channels allow users to provide feedback and suggestions to the platform. The platform should offer convenient feedback channels, such as online feedback forms, customer service hotlines, and social media, and establish a feedback processing mechanism to reply to user feedback in a timely manner and incorporate users' suggestions into the platform's optimization plan. The interface simplicity function emphasizes that the platform interface should be clear and easy to operate. The platform should optimize the interface design, reduce unnecessary functions and elements, highlight core functions, and improve user operation efficiency. At the same time, the interface layout and interaction design should be regularly adjusted according to user feedback. The multi-terminal adaptation emphasizes that the platform supports multiple terminals such as mobile phones, tablets, and computers. The platform should ensure smooth operation on different devices to meet users' needs to use the platform anytime and anywhere. The user customization options allow users to customize functions or information dissemination according to their own needs. The platform should add some customization options, such as information dissemination preference settings, interface theme switching, and functional module customization, to meet users' personalized needs. By reasonably planning and optimizing these indifferent requirement functions, the platform can avoid resource wastage and simultaneously enhance the overall user experience.

5 Conclusion and Outlook

This study conducted a systematic analysis of the requirements for intelligent supervision platforms in farmland abandonment management based on the Kano model, revealing the differentiated characteristics of the requirements of different stakeholders for platform functions, services, and experiences. Through empirical research in a major agricultural county in Jiangxi Province, the requirements were found to be divided into four categories: one-dimensional (such as historical data comparison and land transfer information), must-be (such as policy subsidy information, online customer service and consultation, and data stability), attractive (such as high-precision monitoring and farmland abandonment alert), and indifferent (such as user operation training and user feedback channels). The results indicate that the construction of intelligent supervision platforms should be guided by the requirements, achieving precise functional allocation through layered optimization strategies.

First of all, must-be requirements (such as data stability, policy subsidy information, and online customer service and consultation) reflect users' rigid requirements for the basic performance and service guarantee of the platform. Their absence significantly reduces user trust, but meeting them can only maintain basic satisfaction, indicating that technology development should give priority to ensuring the stability and reliability of the system, while strengthening cooperation with government departments and providing timely and effective technical support. Secondly, the satisfaction degree of one-dimensional requirements (such as historical data comparison, land transfer information, and land transfer transaction support) has a significant linear relationship with user satisfaction, indicating that such functions are the core handle to realize the platform's efficiency. It is worth noting that the strong expected attributes of land transfer-related functions reveal users' urgent needs for optimizing the allocation of land resources, highlighting the important role of the intelligent supervision platform in promoting land transfer. In addition, attractive requirements (such as high-precision monitoring and land abandonment alert) could significantly improve user satisfaction, but they pose greater challenges to the platform's basic architecture. It is necessary to develop them in phases according to resource conditions, gradually provide value-added services for users, and enhance the platform's competitiveness and user experience. Finally, indifferent requirements have a lesser impact on user satisfaction, but the platform still needs to plan them reasonably to avoid resource misallocation and optimize these functions to enhance users' overall experience.

This study provides an empirical basis for the optimal design of intelligent supervision platforms: by focusing on must-be requirements to consolidate the technical foundation, deeply cultivating one-dimensional requirements to strengthen core functions, arranging attractive requirements to enhance value-added services, and optimizing indifferent requirements to avoid resource misallocation, a farmland abandonment governance system that balances efficiency and sustainability can be constructed. At the same time, the study verifies the applicability of the Kano model in the analysis of public governance technology needs and provides a new methodological framework for solving the "technology-requirement" mismatch problem in the field of intelligent agriculture.

Despite the achievements of this study, there are still some limitations. For example, the current case focuses on a single county area, and cross-regional comparative studies could be carried out in the future to explore the heterogeneity rules of requirement structures under different geographical conditions, economic levels, and governance models. Secondly, although the research sample covers multiple types of users such as farmers and business entities, it does not deeply distinguish the requirement differences between small farmers and large-scale business entities. Follow-up studies could construct a requirement hierarchy model based on variables such as land operation scale and digital transformation capability. Finally, since the management of farmland abandonment is policy-driven, the requirements may dynamically evolve with adjustments to food security strategies. In the future, the introduction of a continuous requirement monitoring mechanism can be considered, combined with the quality function deployment method, to achieve iterative optimization of platform functions.

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Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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