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An Integrated Quality Function Deployment Framework Incorporating Interval Type-2 Fuzzy Sets and Behavioural Decision Theory for Optimising Smart Community Technology Adoption

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Abstract: To address the evolving preferences of residents in smart community development and the uncertainty inherent in expert-driven technology adoption decisions, an integrated Quality Function Deployment (QFD) framework has been proposed. This framework combines Interval Type-2 Fuzzy Sets (IT2 FSs), a modified Kano Model, Regret Theory, and the Grey-Entropy Technique for Order Preference by Similarity to Ideal Solution (GETOPSIS). IT2 FSs were employed to accommodate the semantic ambiguity of user demands, enabling more precise interpretation of linguistic input. A refined Kano classification was used to categorise 15 demand indicators, from which 5 Customer Requirements (CRs) and 10 Design Requirements (DRs) were derived. Regret Theory was incorporated to model behavioural biases commonly observed in expert evaluations, particularly the tendency to avoid perceived short-term losses. Additionally, a dynamic weight adjustment mechanism was introduced based on corporate life cycle theory, revealing strategic divergences between early-stage enterprises, which prioritise basic security infrastructure, and mature firms, which emphasise sustainable, energy-efficient technologies. The GETOPSIS method was further enhanced to improve the robustness of technology prioritisation under uncertainty. The principal contributions of this study are threefold: (1) the provision of a QFD framework capable of modelling high-order uncertainty through linguistic variables, (2) the integration of behavioural decision theory to better reflect real-world expert judgement, and (3) the development of an improved GETOPSIS approach for more reliable multi-criteria decision-making. The proposed framework provides theoretical and methodological foundations for advancing adaptive technology adoption strategies in smart communities and may serve as a decision-support tool for policymakers and developers in rapidly evolving urban environments.

Keywords: Quality Function Deployment (QFD); Interval Type-2 Fuzzy Sets (IT2 FSs); Enhanced Kano model; Regret theory; Grey-Entropy TOPSIS (GETOPSIS); Smart community development; User preference analysis; Behavioural decision-making; Dynamic weighting; Technology adoption optimisation

1 Introduction

With the accelerating urbanization process, smart communities are emerging as a pivotal form of future urban living and a new paradigm for sustainable global community development [1]. Centered on residents' well-being, smart communities emphasize social cohesion and humanistic care, leveraging intelligent technologies to deliver convenient, secure, and sustainable living services [2, 3]. Their applications span diverse domains, including personal health, home care, community management, and energy optimization, aiming to address residents' multifaceted needs [4]. Globally, smart community initiatives have been widely implemented [5]. For instance, Japan has developed Community Energy Management Systems (CEMS) integrating smart grids, microgrids, and smart home technologies to optimize energy distribution [6]; the United States employs IoT, sensor networks, and big data analytics to enhance the precision and efficiency of community services [7]; and Singapore has established a "one-stop" smart service platform consolidating functions like intelligent parking and environmental monitoring to improve residents' convenience [8]. However, current smart community development still faces challenges such as low resident engagement, demand-supply mismatches, and funding shortages, resulting in suboptimal user satisfaction [9]. Therefore, this study focuses on the genuine needs of smart community residents, explores how intelligent technologies can enhance their living experience, and provides decision-making support for enterprises to optimize smart community development.

Research on smart community evaluation is currently underway. Existing studies cover multiple aspects, including sustainable development [10], smart community service quality [11], smart home technologies [12], and community security [3]. For example, in the field of smart community services, technological advancements are being utilized to enhance service delivery, with research exploring smart community security monitoring systems [13]. Simultaneously, as smart community construction progresses, increasing attention is being paid to residents' needs. In the currently available literature, Wu et al. [14] employed the Hesitant Fuzzy Decision-Making Trial and Evaluation Laboratory (DEMATEL) method to analyze interrelationships between key demands and determine their weights. However, they neglected the dependency of critical demand importance on decision-making contexts, such as the classification of key demands and their varying impacts on enterprises at different development stages. Wang and Fong [15] adopted a fuzzy Kano model to capture customers' perceived attributes of services and quantify their impact on customer satisfaction levels. Nevertheless, this approach exhibited deficiencies in handling human judgment's fuzziness and certainty. Akbaş and Bilgen [16] proposed an integrated method combining fuzzy QFD and TOPSIS for energy conservation. In practice, decision-making processes are easily influenced by human behavioral factors [17]. After reviewing existing research on QFD decision behaviors and uncertainties, we identified that current QFD models rarely consider: The impact of attribute classification in linguistic uncertainty environments; Behavioral factors of stakeholders and their uncertain decision-making behaviors at different enterprise development stages.

To transcend the limitations of conventional QFD, this study proposes an innovative framework integrating three theoretical-methodological approaches: A CR classification system based on interval type-2 fuzzy Kano modeling; A behavioral decision analysis module incorporating regret theory; And a dynamic prioritization adjustment method using GETOPSIS aligned with enterprise lifecycle stages. This cross-method integration yields a triple theoretical innovation:

1. In demand analysis, IT2 FSs provide a mathematical foundation for addressing requirement semantic ambiguity and data uncertainty in QFD [18, 19], enabling precise classification of requirement attributes through an enhanced Kano questionnaire.

2. In behavioral decision-making, the incorporation of regret theory overcomes the limitations of QFD's traditional rational-agent assumption, effectively capturing behavioral traits such as loss aversion in expert evaluations.

3. In dynamic optimization, the extended GETOPSIS method ensures alignment between technological priorities and strategic enterprise objectives through an adaptive weight-adjustment mechanism tied to lifecycle stages.

The practical significance of this study is particularly salient for China's real estate market, which is undergoing rapid digital transformation. By providing a systematic framework for adopting intelligent technologies, this research offers actionable guidance to real estate enterprises at varying developmental stages—from startups focusing on cost-effective core technologies to mature firms implementing advanced innovative solutions [20, 21]. Moreover, the behavioral insights embedded in the framework can help mitigate common pitfalls in technology investment decisions, such as excessive short-term cost focus or underestimation of long-term value [18, 22].

Building upon the aforementioned theoretical framework and tailored to the unique characteristics of the Smart Property, we developed a Kano questionnaire comprising 15 smart technology demand indicators (Table 1). Utilizing our enhanced interval type-2 fuzzy Kano model, we analyzed valid responses to classify these indicators into four distinct categories: residential decision support demands, living experience optimization demands, personalized service demands and long-term value and sustainability demands.

Table 1. Categorized smart technology demands for real estate applications

Primary Category	Secondary Indicator	Description	References
Residential decision support demands	Immersive digital house-viewing service	Immersive 3D viewing	[23]
	Community real-time price analysis system	ML-driven analytics	[24–26]
	Blockchain-based property contract storage	Title deed clarity	[27]
	Residential risk assessment assistant	Multidimensional analysis	[28]

Primary Category	Secondary Indicator	Description	References
Living experience optimization demands	Smart policy matching and alerts	NLP-based parsing	[29, 30]
	Smart home control platform	IoT automation	[24, 31]
	Community security monitoring network	AI surveillance	[32, 33]
	Intelligent parking navigation system	License plate recognition	[34, 35]
	AI-guided waste sorting	Image recognition	[36]
Personalized service demands	Health monitoring and care service	IoT-assisted services	[37]
	24/7 AI property assistant	Smart Q &A	[38]
	Personalized lifestyle recommendations	Algorithmic recommendations	[39, 40]
	Digital neighbor social platform	Digital interaction	[41, 42]
Long-term value and sustainability demands	Green energy-saving management system	Energy efficiency	[43]
	Community asset value analysis tool	Quantitative evaluation	[44–46]

2 Preliminaries

This section provides a brief explanation of the basic concepts of the Kano model, IT2 FSs, interval grey numbers, regret theory, and QFD.

2.1 Kano Model

Proposed by Kano et al. in 1984, the Kano model employs nonlinear analysis methods to classify CRs, revealing the asymmetric relationship between customer satisfaction and product/service attributes. Its core principle lies in distinguishing requirements into: Must-be, One-dimensional and Attractive. This classification guides enterprises in optimizing resource allocation and enhancing customer satisfaction.

The model utilizes a questionnaire comprising: Functional questions and Dysfunctional questions to collect customer feedback on requirements [47]. Based on statistical results, requirements are categorized into the groups shown in Figure 1.

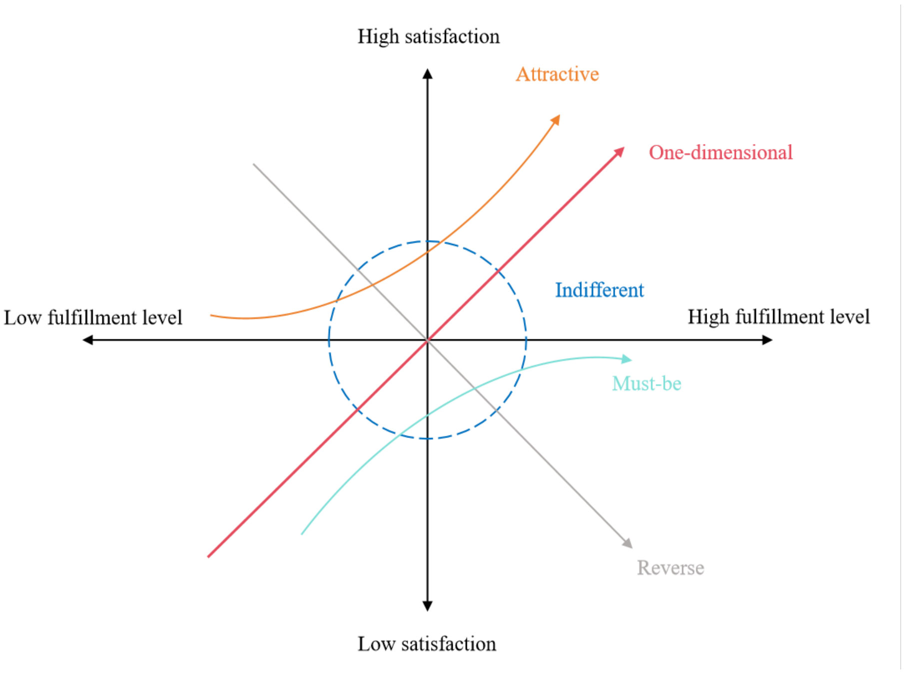

Figure 1. Kano model requirements classification

Must-be (M): If not met, they significantly reduce customer satisfaction, but when met, they merely prevent dissatisfaction without enhancing satisfaction. One-dimensional (O): Satisfaction has a linear relationship with the degree of fulfillment - achieved then satisfied, not achieved then dissatisfied. Attractive (A): Requirements that exceed customer expectations; if not achieved, they do not affect satisfaction, but when achieved, they can significantly improve satisfaction. Indifferent (I): Whether achieved or not, they have no significant effect on satisfaction. Reverse (R): When achieved, they actually cause customer dissatisfaction. Among them, the evaluation methods for each requirement type are shown in Table 2.

Table 2. Kano's evaluation table

CRs		Dysfunctional Question (Attitude When Unmet)				
		Like	**Must-be**	**Neutral**	**Live-with**	**Dislike**
Functional Question (Attitude when met)	Like	Q	A	A	A	O
	Must-be	R	I	I	I	M
	Neutral	R	I	I	I	M
	Live-with	R	I	I	I	M
	Dislike	R	R	R	R	Q

2.2 Interval Type-2 Fuzzy Linguistic Terms

Linguistic variables employ natural language terms (e.g., "high", "medium", "low") to describe the fuzzy attributes of complex systems, providing a theoretical framework to bridge the gap between human cognition and computational processing [48]. Zadeh [48] emphasized that the essence of linguistic variables lies in mapping semantic rules to fuzzy sets. However, traditional Type-1 Fuzzy Sets (T1 FSs) struggle to handle higher-order uncertainties arising from group cognitive differences or dynamic contexts. To address this, Liu and Mendel [49] introduced IT2 FSs, which incorporate upper and lower membership functions to effectively capture the collective cognitive fuzziness of linguistic terms. This makes IT2 FSs a critical tool for managing uncertain decision-making problems.

Definition 1 (General Representation of IT2 FSs) [50]. An IT2 FSs on the universe of discourse X is defined as:

$$\tilde{A} = \Big\{ \big((x, \mu), 1\big) \mid x \in X,\ \mu \in J_x \subseteq [0, 1] \Big\} \tag{1}$$

where, x is the primary variable, μ is the secondary variable, J_x denotes the interval of secondary membership grades for x. The Footprint of Uncertainty (FOU) is jointly delineated by two bounding membership functions: $\underline{\mu}_{\widetilde{A}}(\mathrm{x})$ and $\bar{\mu}_{\widetilde{A}}(\mathrm{x})$. As graphically illustrated in Figure 2, satisfying:

$$\mathrm{FOU}(\widetilde{A}) = \underset{x \in X}{\cup} J_x = \Big\{ (x, u) \mid \underline{\mu}_{\widetilde{A}}(x) \le u \le \bar{\mu}_{\widetilde{A}}(x) \Big\} \tag{2}$$

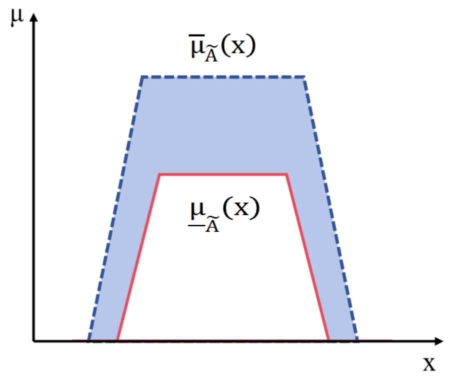

Figure 2. The figue of $\mathrm{FOU}(\widetilde{A})$

Definition 2 (Parametric Representation of Trapezoidal IT2 FSs) [51]. A trapezoidal IT2 FSs $\widetilde{A}$ can be formally represented by its upper and lower trapezoidal membership functions as follows:

$$\widetilde{A}=\left\langle\left(a_{i1}^{U},a_{i2}^{U},a_{i3}^{U},a_{i4}^{U}\right),\left(a_{i1}^{\mathrm{L}},a_{i2}^{\mathrm{L}},a_{i3}^{\mathrm{L}},a_{i4}^{\mathrm{L}};H_{i}^{\mathrm{L}}\right)\right\rangle \tag{3}$$

where, a_i^U and a_i^L $(i=1,2,3,4)$ the positions of the upper and lower trapezoidal vertices, respectively, while H_1^U and $H_1^L \in [0,1]$ represent the membership height parameters. Figure 3 illustrates the geometric structure of a typical trapezoidal IT2-FS.

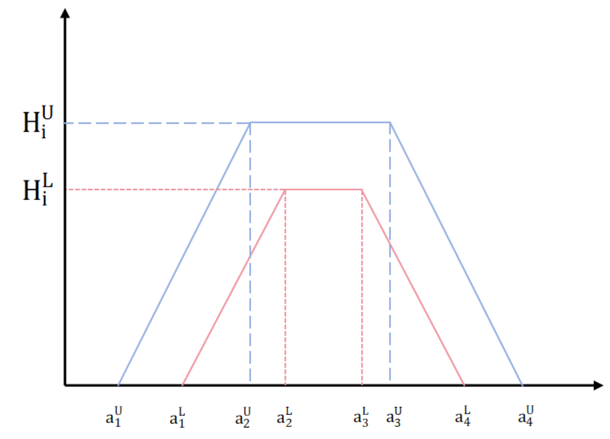

Figure 3. Geometric structure of IT2 FSs

Operational Rules:
For two trapezoidal IT2-FSs $\widetilde{A}_1$ and $\widetilde{A}_2$, their addition result is given by:

$$\widetilde{A}_1 \oplus \widetilde{A}_2=\left(\begin{array}{c}\left(\mathrm{a}_{11}^{\mathrm{U}}+\mathrm{a}_{21}^{\mathrm{U}},\mathrm{a}_{12}^{\mathrm{U}}+\mathrm{a}_{22}^{\mathrm{U}},\mathrm{a}_{13}^{\mathrm{U}}+\mathrm{a}_{23}^{\mathrm{U}},\mathrm{a}_{14}^{\mathrm{U}}+\mathrm{a}_{24}^{\mathrm{U}}\right), \\ \left(\mathrm{a}_{11}^{\mathrm{L}}+\mathrm{a}_{21}^{\mathrm{L}},\mathrm{a}_{12}^{\mathrm{L}}+\mathrm{a}_{22}^{\mathrm{L}},\mathrm{a}_{13}^{\mathrm{L}}+\mathrm{a}_{23}^{\mathrm{L}},\mathrm{a}_{14}^{\mathrm{L}}+\mathrm{a}_{24}^{\mathrm{L}};\min\left(\mathrm{H}_1^{\mathrm{L}},\mathrm{H}_2^{\mathrm{L}}\right)\right)\end{array}\right) \tag{4}$$

When a constant $k \in R+$ is given, its scalar multiplication with $\widetilde{A}$ is defined as:

$$k \otimes \widetilde{A}=\left\langle\left(ka_{i1}^{U},ka_{i2}^{U},ka_{i3}^{U},ka_{i4}^{U}\right),\left(ka_{i1}^{L},ka_{i2}^{L},ka_{i3}^{L},ka_{i4}^{L};H_{1}^{L}\right)\right\rangle \tag{5}$$

Definition 3 (Centroid Interval) [52]: The centroid $C(\widetilde{A})$ of an IT2-FS $\widetilde{A}$ is the interval $[c_l, c_r]$, where:

$$c_l=\frac{\sum_{i=1}^{n} x_i \underline{\mu}_{\widetilde{A}}\left(x_i\right)}{\sum_{i=1}^{n} \underline{\mu}_{\widetilde{A}}\left(x_i\right)}, c_r=\frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{x_i} \bar{\mu}_{\tilde{\mathrm{A}}}\left(x_i\right)}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \bar{\mu}_{\tilde{\mathrm{A}}}\left(x_i\right)}$$

Overall centroid value is:

$$c\left(\widetilde{A}\right)=\frac{c_l+c_r}{2} \tag{6}$$

This computation can be efficiently implemented through the iterative optimization Karnik-Mendel algorithm [53], supporting quantitative comparison of linguistic terms and decision ranking.

2.3 Interval Grey Numbers

In uncertain decision-making problems, due to the limitations of evaluators' cognitive capabilities, it is often only possible to determine the bounds of parameters rather than obtain precise values. Such uncertain quantities with interval characteristics are referred to as interval grey numbers. From a mathematical perspective, a grey number is an uncertain value that lies within a specific interval or a general numerical set. Its standard representation is $\otimes \in [a,b]$, where a≤b.

Definition [54]: Let there exist a grey number $\otimes \in [a,b]$, with a value background domain Ω, where $\mu(\cdot)$ is a measurable function. Then we define: $g^0 = \max_{x\in[a,b]} \mu(x)$ as the kernel of the interval grey number $\otimes$, $\gamma = 1-\frac{\mu(g^0)}{\mu(\Omega)}$ as the grey degree of the interval grey number $\otimes$, $\rho=\frac{\mu([a,b])}{\mu(\Omega)}$ as the interval confidence degree of the interval grey number $\otimes$.

2.4 Regret Theory

Proposed by Bell [55], regret theory incorporates psychological behavioral factors of decision-makers (DMs) into the utility analysis framework. The perceived utility function V of a DM consists of two components:

$$V_{ab} = U_a + R\left(U_a - U_b\right) \tag{7}$$

where, U_a and U_b represent the utility values obtained from selecting alternative A and forgoing alternative B, respectively; R(·) denotes a monotonically increasing concave function that quantifies the regret-rejoice effect. The decision-making process in this theory is primarily influenced by two factors: the anticipation of potential regret or rejoice emotions, and the DM's tendency to avoid alternatives that may induce strong regret.

2.5 QFD

QFD [47], is a systematic product development methodology. Its core mechanism utilizes the House of Quality (HoQ) to translate Voice of Customer (VoC) into actionable technical characteristics [56]. As shown in Table 3, the HoQ typically comprises seven core components.

Table 3. Seven core components of the HoQ

Component Category	Symbol Notation	Definition
CRs	*WHATs*	Raw customer needs obtained through market research.
DRs	*HOWs*	Engineering parameters that fulfill CRs.
CRs Priority Weights	W_i	Quantified priority values for each requirement.
CRs-DRs Relationships	R_{ij}	Degree to which technical characteristics satisfy each requirement.
Competitive Benchmarking	B_{ik}	Performance comparison between our product and competitor k on requirement i.
DRs Interdependencies	D_{kj}	Synergistic or conflicting relationships between technical characteristics.
DRs Final Priorities	P_j	Comprehensive weighted calculation results.

3 QFD Improvement Model Integrating Linguistic Uncertainty and Behavioral Decision-Making

3.1 Proposed QFD Model Framework

To address the key challenges of traditional QFD methods, we propose an integrated model developed in three stages under interval type-2 fuzzy uncertainty, as illustrated in Figure 4.

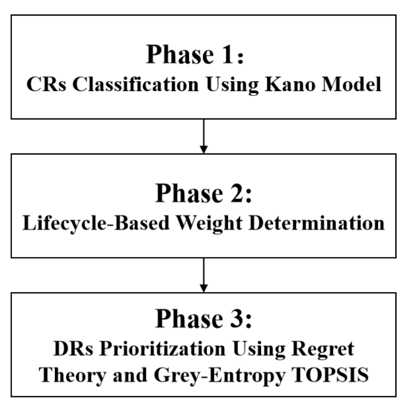

Figure 4. QFD model framework

Phase 1: CRs Classification Using Kano Model

Typically employing questionnaire surveys to collect CRs, we designed Kano questionnaires using interval type-2 fuzzy linguistic terms to gather customer preferences for CRs. Each CR $(\mathrm{CR}_1, \mathrm{CR}_2, \ldots, \mathrm{CR}_1, \ldots, \mathrm{CR}_m)$ is evaluated through functional and dysfunctional questions (Table 2). To handle uncertainty, responses are converted into trapezoidal IT2 FSs. Finally, the categories of m CRs are determined through Kano evaluation tables.

Phase 2: Weight Determination Considering Enterprise Lifecycle

We recognize that enterprises at different development stages exhibit significant differences in prioritizing key resources (CRs) under limited budgets: startups prioritize technological breakthroughs, growth-stage enterprises emphasize market expansion, mature enterprises focus on operational optimization, while declining enterprises concentrate on survival strategies. Based on this understanding, we calculate normalized weights $\mathrm{w} = (\mathrm{w_1},\ \mathrm{w_2}, \ldots,\ \mathrm{w_m})$ for m CRs. The weighting mechanism incorporates lifecycle adjustment factors (startup, growth, maturity, decline), interval type-2 fuzzy aggregation of expert evaluations, and a normalization process ensuring $\sum \mathrm{w_i} = 1$.

Phase 3: DRs Ranking via GETOPSIS and Regret Theory

Through expert evaluations using interval type-2 fuzzy linguistic terms, we construct a correlation matrix between m CRs $(\mathrm{CR_1}, \mathrm{CR_2}, \ldots, \mathrm{CR_m})$ and n DRs $(\mathrm{DR_1}, \mathrm{DR_2}, \ldots, \mathrm{DR_j}, \ldots, \mathrm{DR_n})$. The regret-based GETOPSIS method is then applied to determine priorities for n DRs, followed by final ranking.

3.2 Classification of CR Values Using Kano Model Based on Interval Type-2 Fuzzy Linguistic Variables

To determine the categories of m CRs, we designed a Kano questionnaire distributed to a targeted group of customers to collect their preference levels for these m requirements. The questionnaire employs linguistic terms such as “very like”, “expected”, “neutral”, “reluctantly accept”, and “very dislike”. Traditional methods typically rely on the classification criteria outlined in Table 2, where the category of each CR is determined by statistically analyzing the frequency of each linguistic evaluation option. However, in practice, situations often arise where a particular requirement receives equal frequencies across multiple evaluation options, making it difficult to accurately classify its category based solely on simple frequency statistics. To address this issue, this study introduces the IT2 FSs method to transform qualitative linguistic evaluations into quantitative linguistic variables. This allows for precise classification of CRs based on the operational rules of IT2 FSs.

It is important to note that the IT2 FSs corresponding to linguistic variables may vary depending on the research subject and application context. Although this study focuses on potential smart community users’ preferences for smart technologies—a different context from the online shopping scenario examined in reference by Wu et al. [57]—the method proposed in it for constructing seven interval type-2 fuzzy linguistic variables remains highly valuable as a reference. To align with the characteristics of this study, we selected five linguistic variables with high adaptability and incorporated them into the Kano model’s evaluation framework. The membership function distributions of these five specialized trapezoidal interval type-2 fuzzy linguistic variables are illustrated in Figure 5, and their specific parameter representations are detailed in Table 4. Where, the x-axis represents the quantitative scale of linguistic variables, and the y-axis indicates the membership degree of a linguistic term to a specific evaluation value. The linguistic sets are designated as: L, M, N, W, D.

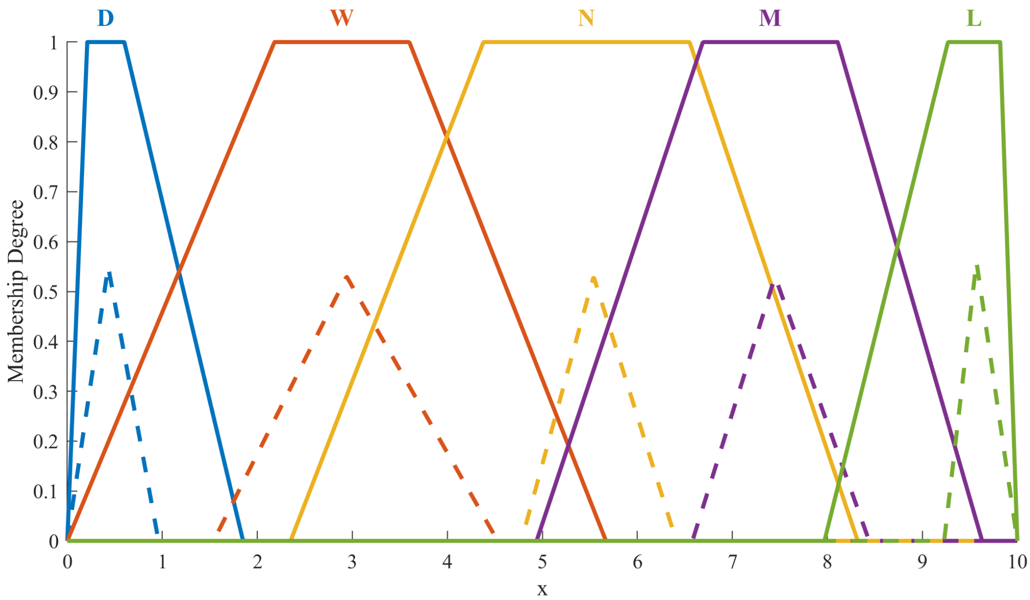

Figure 5. The membership function of five linguistic variables [57]

Table 4. Interval type-2 fuzzy linguistic variables for Kano questionnaire

Linguistic Terms	Trapezoidal Interval Type-2 Fuzzy Set
L	((7.97, 9.27, 9.82, 10)(9.23, 9.57, 9.57, 10; 0.56))
M	((4.94, 6.69, 8.11, 9.63)(6.58, 7.45, 7.45, 8.44; 0.53))
N	((2.35, 4.38, 6.55, 8.32)(4.78, 5.54, 6.41; 0.53))
W	((0, 2.18, 3.60, 5.67)(1.54, 2.94, 2.94, 4.53; 0.53))
D	((0, 0.21, 0.60, 1.85)(0, 0.43, 0.43, 0.96; 0.55))

Assuming we distributed k survey questionnaires and obtained 1 valid sample after quality screening (where $1 \leq$ k must be satisfied). During data processing, we first eliminate invalid "Questionable" questionnaires containing logical contradictions. After removing invalid responses, we record the frequencies of each CRi receiving the five evaluation levels in functional assessment $(\widetilde{U_i})$ and dysfunctional assessment $(\widetilde{U_i'})$: L, M, N, W and D. These frequencies are denoted respectively as: $F_L^i, F_M^i, F_N^i, F_W^i$ and F_D^i (functional) and $D_L^i, D_M^i, D_N^i, D_W^i$ and D_D^i (dysfunctional). The composite functional evaluation $\widetilde{U_i'}$ and dysfunctional evaluation $\widetilde{U_i'}$ for CR$_i$ are then calculated using the following formulas:

$$\widetilde{U_i} = \frac{F_L^i \times \widetilde{L} + F_M^i \times \widetilde{M} + F_N^i \times \widetilde{N} + F_W^i \times \widetilde{W} + F_D^i \times \widetilde{D}}{l} \tag{8}$$

$$\widetilde{U_i'} = \frac{D_L^i \times \widetilde{L} + D_M^i \times \widetilde{M} + D_N^i \times \widetilde{N} + D_W^i \times \widetilde{W} + D_D^i \times \widetilde{D}}{l} \tag{9}$$

In these formulas, the parameters satisfy 1≤l≤k, where $F_L^i, F_M^i, F_N^i, F_W^i, F_D^i$ and $D_L^i, D_M^i, D_N^i, D_W^i, D_D^i$ respectively represent the statistical frequencies of CRi receiving linguistic evaluations L,M,N,W,D for both functional and dysfunctional questions. The terms $\widetilde{L}, \widetilde{M}, \widetilde{N}, \widetilde{W}, \widetilde{D}$ correspond to the IT2 FSs for linguistic items L,M,N,W,D as defined in Table 4.

Subsequently, following Eq. (6), we calculate the centroid-based distances between each linguistic term and either $\widetilde{U_i}$ (functional evaluation) or $\widetilde{U_i'}$ (dysfunctional evaluation).

$$d\left(\widetilde{L}, \widetilde{U_i}\right) = \left| c\left(\widetilde{L}\right) - c\left(\widetilde{U_i}\right) \right| \tag{10}$$

Consistent with the Kano evaluation matrix in Table 2, the category of CRi is determined through minimum distance matching. For example: $\min\left\{\mathrm{d}\left(\widetilde{\mathrm{M}}, \widetilde{\mathrm{U}}_\mathrm{i}\right), \mathrm{d}\left(\widetilde{\mathrm{N}}, \widetilde{\mathrm{U}}_\mathrm{i}\right), \ldots\right\} = \mathrm{d}\left(\widetilde{\mathrm{M}}, \widetilde{\mathrm{U}}_\mathrm{i}\right)$ and $\min\left\{\mathrm{d}\left(\widetilde{\mathrm{D}}, \widetilde{\mathrm{U}}_\mathrm{i}'\right), \ldots\right\} = \mathrm{d}\left(\widetilde{\mathrm{D}}, \widetilde{\mathrm{U}}_\mathrm{i}'\right)$, then CRi is classified as a Must-be (M) attribute.

3.3 Determining Requirement Weights Based on Enterprise Development Stage

Building upon the results obtained from the Kano model, we employ the better-worse coefficient [58] to quantify the objective importance of each requirement. Following the framework presented in Table 2, we first calculate the proportion of each CR belonging to the following Kano categories: A, O, M, I, R and Q. The classification ratios are computed as:

$$\begin{aligned}
r_A^i &= \left[\max(a_{uj}) - d(\widetilde{L}, \widetilde{U}_i)\right] \times \left[3\max(a_{uj}) - d(\widetilde{M}, \widetilde{U}_i) - d(\widetilde{N}, \widetilde{U}_i) - d(\widetilde{W}, \widetilde{U}_i)\right] \\
r_O^i &= \left[\max(a_{uj}) - d(\widetilde{L}, \widetilde{U}_i)\right] \times \left[\max(a_{uj}) - d(\widetilde{D}, \widetilde{U}_i')\right] \\
r_M^i &= \left[\max(a_{uj}) - d(\widetilde{D}, \widetilde{U}_i)\right] \times \left[3\max(a_{uj}) - d(\widetilde{M}, \widetilde{U}_i) - d(\widetilde{N}, \widetilde{U}_i) - d(\widetilde{W}, \widetilde{U}_i')\right] \\
r_I^i &= \left[3\max(a_{uj}) - d(\widetilde{M}, \widetilde{U}_i) - d(\widetilde{N}, \widetilde{U}_i) - d(\widetilde{W}, \widetilde{U}_i)\right] \times \left[3\max(a_{uj}) - d(\widetilde{M}, \widetilde{U}_i') - d(\widetilde{N}, \widetilde{U}_i') - d(\widetilde{W}, \widetilde{U}_i')\right] \\
r_R^i &= \left[\max(a_{uj}) - d(\widetilde{L}, \widetilde{U}_i)\right] \times 4 \times \left[\max(a_{uj}) - d(\widetilde{M}, \widetilde{U}_i) - d(\widetilde{N}, \widetilde{U}_i) - d(\widetilde{W}, \widetilde{U}_i) - d(\widetilde{B}, \widetilde{U}_i)\right] \\
&\quad + \left[\max(a_{uj}) - d(\widetilde{D}, \widetilde{U}_i)\right] \times \left[3\max(a_{uj}) - d(\widetilde{M}, \widetilde{U}_i') - d(\widetilde{N}, \widetilde{U}_i') - d(\widetilde{W}, \widetilde{U}_i')\right] \\
r_Q^i &= \left[\max(a_{uj}) - d(\widetilde{L}, \widetilde{U}_i)\right] \times \left[\max(a_{uj}) - d(\widetilde{L}, \widetilde{U}_i')\right]
\end{aligned} \tag{11}$$

where, $\max(a_{uj})$ represents the maximum parameter among the interval type-2 fuzzy linguistic variables L,M,N,W,D. This serves as a reference point for measuring the deviation of each CR's classification. The greater the deviation, the lower the probability that the CR belongs to a particular attribute.

$$S_i = \frac{r_A^i + r_O^i - r_Q^i}{r_A^i + r_O^i + r_M^i + r_I^i} \tag{12}$$

where, the satisfaction coefficient S_i reflects the positive contributions of attractive attributes (A) and one-dimensional attributes (O) in its numerator, while the denominator performs normalization.

The dissatisfaction coefficient DS_i can be interpreted as the dissatisfaction level when CRs is excluded:

$$DS_i = -\frac{r_O^i + r_M^i - r_Q^i}{r_A^i + r_O^i + r_M^i + r_I^i} \tag{13}$$

where, the negative sign ensures positive output values, with larger numerical values indicating higher dissatisfaction levels. Based on the two-dimensional evaluation results, the higher the satisfaction S_i and dissatisfaction DS_i, the more critical CRs become. Consequently, standardized weights are calculated using coupling analysis:

$$\omega_i = \frac{S_i \times D\ S_i}{\sum_{j=1}^{m} (S_j \times D\ S_j)} \tag{14}$$

In the enterprise operation process, although the objective weights of CRs originate from customer evaluation data, actual decision-making requires comprehensive consideration of the enterprise's lifecycle stage and management's risk preferences [59]. According to related research, the enterprise lifecycle can typically be divided into four distinct phases: Survival stage, Growth stage, Maturity stage, and Decline stage, as illustrated in Figure 6. Enterprises at different development stages often exhibit differentiated strategic priorities and resource allocation preferences.

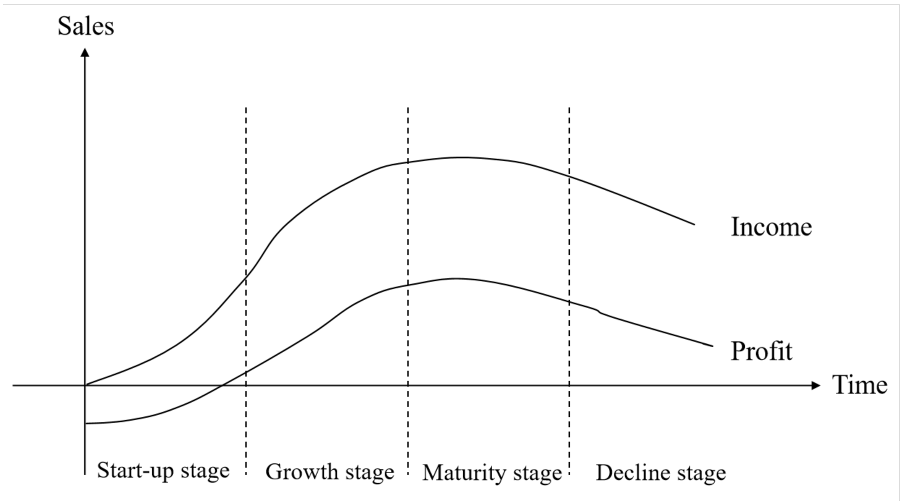

Figure 6. Four stages of enterprise lifecycle

For routine business operations, the Q and I attributes hold limited practical significance. Therefore, we focus primarily on adjusting the weights of the three key attribute categories: M, O, and A. Assuming the enterprise is currently at lifecycle stage s (where s$\in$ {start-up, growth, maturity, decline}), we define the reference weight set R_s as the minimum weight collection for a given attribute category (e.g., M, O, A) at that specific stage.

The DM's perceived utility of selecting CRs consists of two components: baseline utility and the regret-rejoice effect:

$$V_i = U_i + R\,(U_i - U_{ref}) \tag{15}$$

where, $U_i = \omega_i, U_{ref}$=min(Rs). The function $R(\cdot)$, a monotonically increasing concave function reflecting regret-aversion tendency, adopts the classical form:

$$R\left(\Delta \text{ U}\right)=1-e^{-\gamma\Delta U},\gamma>0 \tag{16}$$

The parameter γ represents the regret sensitivity coefficient. While Kahneman and Tversky [60] suggested a value of γ=0.88, this parameter can be adjusted based on practical circumstances. The reference sets and corresponding γ values for each lifecycle stage are presented in Table 5.

Table 5. Parameter configuration of regret theory across lifecycle stages

Lifecycle Stage	R$_s$	γ Value	Behavioral Mechanism	Theoretical Basis
Start-up	M	1	Strong regret aversion	Survival pressure theory [55]
Growth	O	0.88	Baseline sensitivity	Classical regret theory [60]
Maturity	A	0.75	Weak regret effect	Resource slack theory [59]
Decline	M	1.2	Extreme aversion	Crisis decision studies [55]

The setting of the regret theory parameter γ for different lifecycle stages was rigorously validated through the Delphi expert survey method. We invited 12 senior executives from the property industry (with an average of 10 years of professional experience, covering developers, agencies, and investors) to conduct three rounds of back-to-back evaluations. The first round involved feasibility scoring (1-5 points) of preset γ values, the second round combined typical decision-making cases to justify parameter ranges, and the third round reached final consensus. The final results showed that: for the startup phase, γ=1.0 (with 83% of experts agreeing it reflects strong risk aversion under survival pressure); for the growth phase, γ=0.88 (75% of experts believed this value meets the balanced needs during expansion); for the maturity phase, γ=0.75 (92% of experts supported this value as it reflects moderate innovation preference under conditions of resource redundancy); and for the decline phase, γ=1.2 (83% of experts agreed this captures extreme avoidance characteristics in crisis decision-making). Therefore, this study adopts these expert-consensus-validated γ parameter values to ensure the model accurately reflects the decision-making behavioral characteristics of enterprises at different stages.

Building upon the reference points and parameter concepts from regret theory, we adjust the target weights ω_i(i=1,2,. . . ,m). According to Eq. (7), the adjusted weight ω_i' for CRs at a specific enterprise development stage can be calculated as follows:

$$\omega_i'=\begin{cases} V_i & \text{If } \omega_i\in R_s \\ V_i\cdot\left(1-\frac{|\omega_i-U_{\text{ref}}|}{\max(R_s)}\right) & \text{or,} \end{cases} \tag{17}$$

In this process, the reference set is selected based on the enterprise's lifecycle stage. When $\omega_i\in R_s$, the perceived utility is directly calculated as $V_i=U_i+R\left(U_i-U_{ref}\right)$. Otherwise, the utility value is proportionally reduced to penalize deviations from the reference point using $\frac{|\omega_i-U_{ref}|}{max(R_s)}$.The adjusted weight ω_i' must satisfy the condition ω_i' ∈[0,1]. To ensure the validity of weight calculation, we set ω_i'=0 when ω_i' <0. Finally, the normalized weight μ_i for CRs can be calculated using the following formula:

$$\mu_i=\frac{\omega_i'}{\sum_{i=1}^m\omega_i'} \tag{18}$$

where, μ_i[0,1] and the sum of all normalized weights satisfies $\sum_{i=1}^m\mu_i$.

3.4 DR Prioritization Using Regret-Based GETOPSIS Method

Under uncertain environments, we account for DMs' behavioral characteristics when prioritizing DRs by integrating regret theory and interval grey numbers into an extended TOPSIS framework. Experts evaluate the CR-DR correlations using interval type-2 fuzzy linguistic variables. The architecture of the regret-based GETOPSIS method is illustrated in Figure 7.

To obtain more refined expert evaluation information, we adopt the seven interval type-2 fuzzy linguistic variables defined by Wu et al. [57] to assess the correlations between CRs and DRs. The membership functions of these linguistic variables are shown in Figure 8, and their corresponding IT2 FSs are listed in Table 6. Among them, "High" indicates a strong correlation between CR and DR. The priority order of all linguistic variables satisfies the following relationship: EH > VH > H > M > L > VL > EL. Where, the x-axis represents the quantitative scale of linguistic variables, and the y-axis indicates the membership degree of a linguistic term to a specific evaluation value. The linguistic sets are designated as: EH, VH, H, M, L, VL, EL.

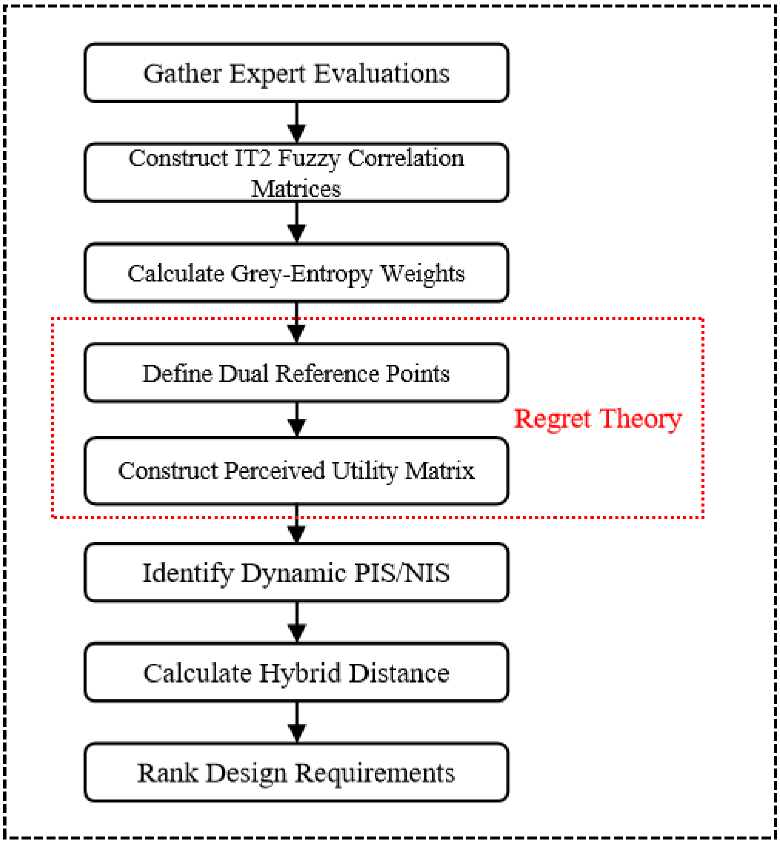

Figure 7. Framework of the regret-based GETOPSIS method

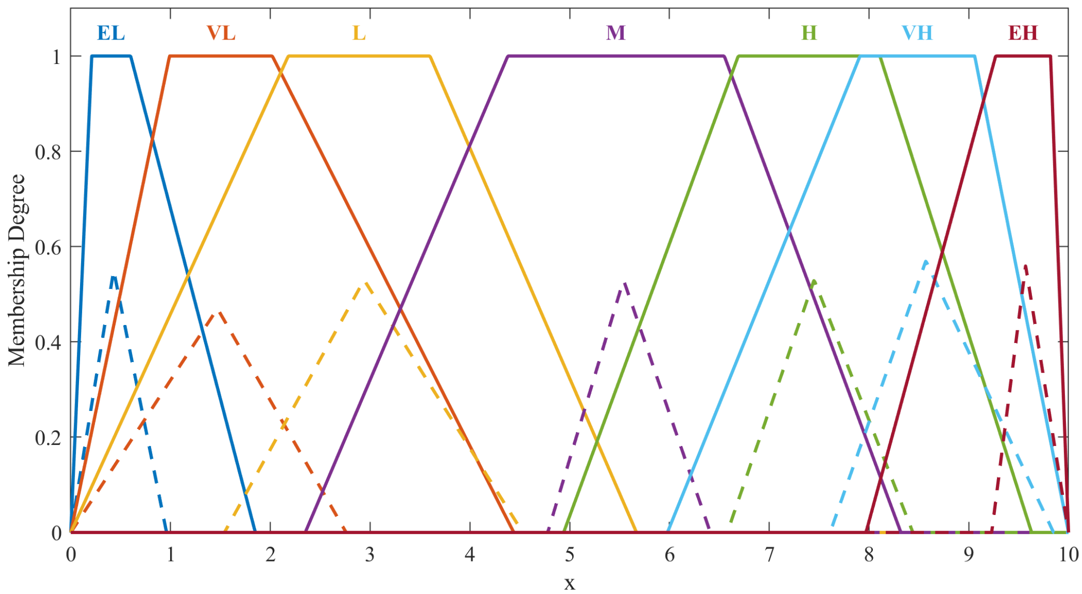

Figure 8. Membership functions of the seven linguistic variables

Table 6. Interval type-2 fuzzy linguistic terms for evaluating CR-DR correlations

Linguistic Terms	Trapezoidal Interval Type-2 Fuzzy Set
Extremely High (EH)	((7.97, 9.27, 9.82, 10)(9.23, 9.57, 9.57, 10; 0.56))
Very High (VH)	((5.98, 7.91, 9.06, 10)(7.61, 8.57, 8.57, 9.85; 0.57))
High (H)	((4.94, 6.69, 8.11, 9.63)(6.58, 7.45, 7.45, 8.44; 0.53))
Medium (M)	((2.35, 4.38, 6.55, 8.32)(4.78, 5.54, 6.41; 0.53))
Low (L)	((0, 2.18, 3.60, 5.67)(1.54, 2.94, 2.94, 4.53; 0.53))
Very Low (VL)	((0, 0.99, 2.02, 4.44)(0, 1.47, 1.47, 2.76; 0.47))
Extremely Low (EL)	((0, 0.21, 0.60, 1.85)(0, 0.43, 0.43, 0.96; 0.55))

Based on evaluations from multiple experts using interval type-2 fuzzy linguistic variables to assess CR-DR relationships, we first construct individual correlation matrices for each expert. Assuming there are s experts participating in the evaluation, the assessment results of the k-th expert d_k (where $1 \leq$ k $\leq$s) can be represented as an m×n interval type-2 fuzzy correlation matrix:

$$\tilde{A}^k = \left(\tilde{a}_{ij}^k\right)_{m\times n} = \begin{bmatrix} \tilde{a}_{11}^k & \tilde{a}_{12}^k & \cdots & \tilde{a}_{1n}^k \\ \tilde{a}_{21}^k & \tilde{a}_{22}^k & \cdots & \tilde{a}_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{m1}^k & \tilde{a}_{m2}^k & \cdots & \tilde{a}_{mn}^k \end{bmatrix} \tag{19}$$

The matrix element $\widetilde{a}_{ij}^k$ $(i = 1, 2, \ldots, m; j = 1, 2, \ldots, n)$ represents expert d_k's assessment of the correlation between CRi and DRj, with values drawn from the predefined interval type-2 fuzzy linguistic variable set (EH $>$ VH $>$ H $>$ M $>$ L $>$ VL $>$ EL).

The interval type-2 fuzzy weighted average (IT2FWA) operator is employed to synthesize expert judgments:

$$\widetilde{r}_{ij} = \left\langle \frac{\sum_{k=1}^{s} \mu_k \cdot \underline{a}_{ij}^k}{\sum_{k=1}^{s} \mu_k}, \frac{\sum_{k=1}^{s} \mu_k \cdot \overline{a}_{ij}^k}{\sum_{k=1}^{s} \mu_k} \right\rangle \tag{20}$$

where, expert weights μ_k are derived via an enhanced entropy-weight method:

$$\mu_k = \frac{1 - \frac{1}{lnl} \sum_{i=1}^{m} \sum_{j=1}^{n} \widetilde{p}_{ij}^k ln\widetilde{p}_{ij}^k}{\sum_{k=1}^{s} \left(1 - \frac{1}{lnl} \sum_{i=1}^{m} \sum_{j=1}^{n} \widetilde{p}_{ij}^k ln\widetilde{p}_{ij}^k\right)} \tag{21}$$

where, $\tilde{p}_{ij}^k c = \left(\tilde{a}_{ij}^k\right) / \sum_{i,j} c\left(\tilde{a}_{ij}^k\right)$, and c(·) is the centroid function defined in Eq. (6).

Then the aggregated results are standardized as interval grey numbers:

$$\otimes r_{ij} = \left[r_{ij}^L, r_{ij}^U\right] \tag{22}$$

where, with bounds computed via the Karnik-Mendel algorithm [53].

To balance enterprise lifecycle stage weights w_j^{LC} with data objectivity, we propose a grey-entropy-lifecycle collaborative weighting approach. For computational convenience, we directly invited experts to rate the importance of CRs across the four lifecycle stages. For each w_j^{LC}, we divided individual expert ratings by the total score of their corresponding lifecycle stage, then calculated the average across all experts, and finally normalized the results. The kernel of interval grey numbers is computed as:

$$c\left(\otimes r_{ij}\right) = \frac{r_{ij}^- + r_{ij}^+}{2} \tag{23}$$

where, $r_{ij}^- = r_{ij}^L$ and $r_{ij}^+ = r_{ij}^U$, represent the lower and upper bounds of the standardized interval grey number $\otimes r_{ij}$.

Based on kernel values, the information entropy is derived:

$$E_j = -\frac{1}{lnm}\sum_{i=1}^{m}\rho_{ij}ln\rho_{ij}, \rho_{ij} = \frac{c\left(\otimes r_{ij}\right)}{\sum_{i=1}^{m} c\left(\otimes r_{ij}\right)} \tag{24}$$

Note: If $c\left(\otimes r_{ij}\right) = 0$, enforce $\rho_{ij} = \epsilon$ (where ϵ is a minimal positive value to avoid singularity)

The grey-entropy weights are calculated as:

$$w_j^{grey} = \frac{1 - E_j}{\sum_{j=1}^{n}\left(1 - E_j\right)} \tag{25}$$

The comprehensive weights are fused via geometric mean:

$$w_j = \frac{\sqrt{w_j^{LC} \times w_j^{grey}}}{\sum_{j=1}^{n}\sqrt{w_j^{LC} \times w_j^{grey}}} \tag{26}$$

The baseline utility is formulated using Kahneman and Tversky's [60] power function from prospect theory:

$$u\left(\otimes r_{ij}\right) = \left(c\left(\otimes r_{ij}\right)\right)^{\alpha} \tag{27}$$

where, α=0.88 captures diminishing sensitivity to gains.

Next, we need to establish a dual-dimensional reference system for ideal solutions. The Positive Ideal Solution (PIS) is determined using the maximization principle, selecting the best performance of each DR across all expert evaluations:

$$\otimes r_j^{+} = \max_i c\left(\otimes r_{ij}\right) \tag{28}$$

Correspondingly, the Negative Ideal Solution (NIS) is constructed using the minimization principle:

$$\otimes r_j^{-} = \min_c\left(\otimes r_{ij}\right) \tag{29}$$

Definition of the Nonlinear Adjustment Function for Regret and Rejoice Effects:

$$R_{ij} = 1 - exp\left(-\delta \times \left|u\left(\otimes r_{ij}\right) - u\left(\otimes r_j^{+}\right)\right|\right) \tag{30}$$

With δ=0.5, when $u\left(\otimes r_{ij}\right) \geq \otimes r_j^{+}, R_{ij}$ >0 indicates the rejoice effect (positive utility gain from exceeding expectations); when $u\left(\otimes r_{ij}\right) \leq \otimes r_j^{+}, R_{ij}$ <0 indicates the regret effect (negative utility loss from underperformance).

Finally, perceived Utility Matrix Construction:

$$v_{ij} = u\left(\otimes r_{ij}\right) + R_{ij} \tag{31}$$

Based on these reference points, we employ an enhanced Euclidean distance formula to measure the closeness of each DR alternative to the ideal solutions. The positive ideal distance $\left(D_i^{+}\right)$ and negative ideal distance $\left(D_i^{-}\right)$ are calculated as follows:

$$D_i^{+} = \sqrt{\sum_{j=1}^{n} w_j\left(v_{ij} - v_j^{+}\right)^2}, v_j^{+} = \max_i v_{ij} \tag{32}$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{n} w_j\left(v_{ij} - v_j^{-}\right)^2}, v_j^{-} = \min_i v_{ij} \tag{33}$$

where, v_{ij} denotes the perceived utility value of the i-th DR with respect to the j-th CR; w_j represents the comprehensive weight of the j-th CR.

Based on the distance measures D_i^+ and D_i^-, the priority ratio C_i for each design alternative DR$_j$(1≤j≤n) is computed as:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{34}$$

The priority ratio reflects the relative closeness of design alternatives to the ideal solutions. Ultimately, the alternatives are ranked in descending order of their ratios - higher values indicate superior solutions that should receive higher implementation priority.

When evaluating CR-DR relationships, our regret theory-integrated TOPSIS method thoroughly incorporates experts' behavioral characteristics. Unlike conventional approaches, this method employs a three-stage framework of "behavioral adjustment - distance quantification - relative ranking," theoretically reconciling QFD's technical rigor with the practical rationality of behavioral decision-making.

3.5 The Main Process Steps of the Proposed QFD Model

Considering expert behavioral factors in determining requirement weights and prioritizing technical solutions, the proposed QFD model follows the key process illustrated in Figure 9.

We first conducted a questionnaire survey among potential smart community users based on the 15 indicators proposed in Table 1. The top five indicators with the highest response frequencies were selected as CRs. These 5 CRs were then analyzed using an improved interval type-2 fuzzy Kano model applied to the valid collected questionnaires. For the remaining 10 indicators, domain experts were invited to assess their suitability as technology solutions related to the requirements. Based on their analysis, the final DRs were determined. Subsequently, the technical solutions are prioritized according to the workflow depicted in Figure 9.

Phase I: Kano-Based Requirement Classification Using Interval Type-2 Fuzzy Linguistic Variables.

Step 1: Collecting Customer Fuzzy Linguistic Evaluations of Requirements.

A Kano questionnaire containing m requirements is designed with reference to Table 2, employing linguistic terms such as "very appealing" and "taken for granted" (see Table 4). The survey is distributed to h targeted real estate customers. After excluding invalid responses, l valid questionnaires are obtained.

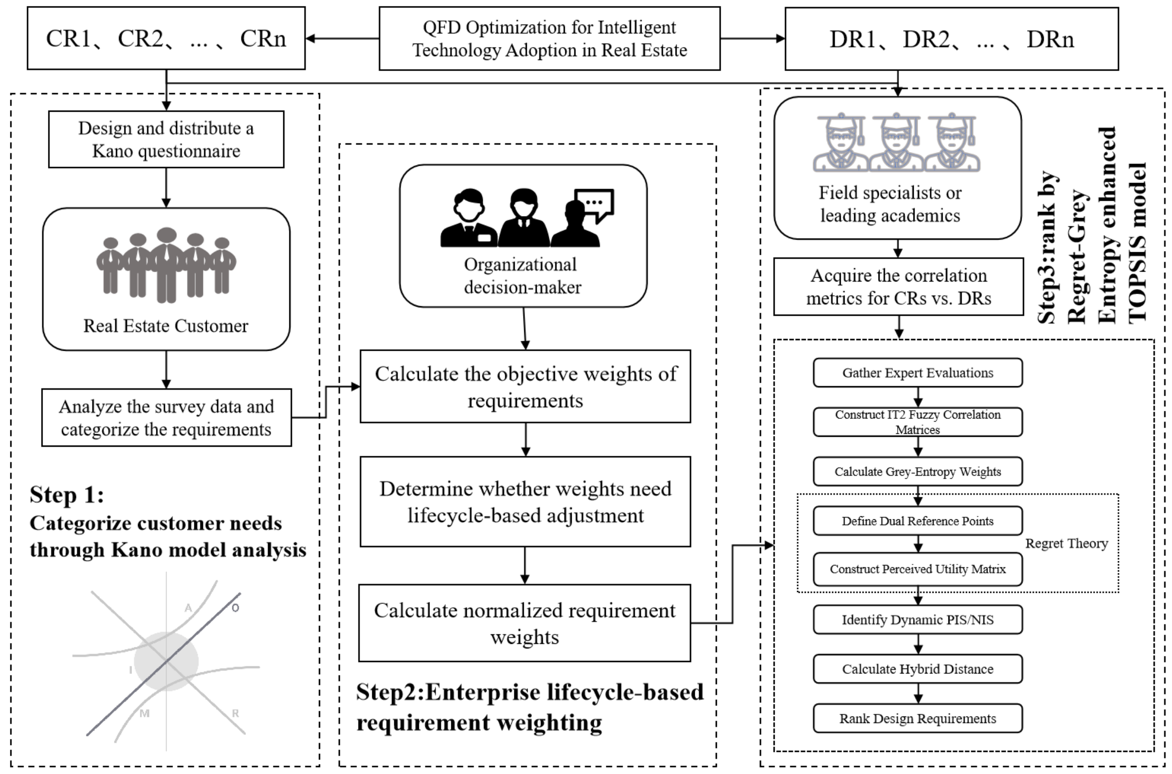

Figure 9. Proposed QFD flowchart

Step 2: Requirement Classification Based on Interval Type-2 Fuzzy Set Distance.

The linguistic evaluation frequencies of each requirement (CRi) under both functional and dysfunctional questions are aggregated from the l respondents. The comprehensive functional ($\widetilde{U_i}$) and dysfunctional ($\widetilde{U_i'}$) evaluation values for each CRi are computed using Eqs. (8) and (9). Subsequently, the requirement category is determined by calculating its distance from Kano linguistic terms via Eq. (10).

Phase II: Determination of Requirement Weights Considering Enterprise Lifecycle.

Step 1: Calculation of Objective Requirement Weights.

The satisfaction (S_i) coefficient and dissatisfaction(DS_i) coefficient for each requirement (CRi) are computed using Eqs. (12) and (13), followed by the determination of objective weights via Eq. (14).

Step 2: Lifecycle-Based Weight Adjustment Assessment.

The enterprise's current development stage (start-up, growth, maturity, or decline) is identified based on operational conditions. The necessity for weight adjustment across requirement categories is evaluated according to stage-specific priority rules.

Step 3: Computation of Normalized Requirement Weights.

For weights requiring adjustment, the reference points are determined based on the regret theory parameters in Table 5, and the adjusted weights ω_i' are calculated using Eq. (17). Finally, the normalized weights μ_i are obtained through Eq. (18).

Phase III: Prioritization of Technical Solutions Based on Regret-GETOPSIS.

Step 1: Construction of Standardized Interval Type-2 Fuzzy Relation Matrix.

Invite s experts (e.g., real estate professionals and smart technology experts) to evaluate the correlation between requirements and technical solutions using the interval type-2 fuzzy linguistic terms from Table 6. Construct individual correlation matrices for each expert d_k: $\widetilde{A}^k = \left(\widetilde{a}_{ij}^k\right)_{m\times n}$.

Step 2: Aggregate Expert Evaluations and Convert to Interval Grey Numbers.

Aggregate individual matrices using the interval type-2 fuzzy weighted average operator Eq. (20). Determine expert weights through the improved entropy weight method Eq. (21). Convert the aggregated results into interval grey numbers $\otimes r_{ij}$ using Eq. (22).

Step 3: Determine Comprehensive Weights Integrating Grey Entropy and Lifecycle Factors.

Calculate grey entropy weights w_j^{grey} using Eqs. (24) and (25). Fuse with lifecycle stage weights w_j^{LC} through geometric mean Eq. (26). Obtain final comprehensive weights w_j.

Step 4: Construct Behavioral Decision Matrix Incorporating Regret Theory.

Determine positive and negative ideal solutions (PIS and NIS) using Eqs. (28) and (29). Calculate perceived utility values v_{ij} including regret/rejoice effects through Eqs. (27), (30) and (31).

Step 5: Determine Technical Solution Priorities.

Calculate distances D_i^+ and D_i^- between solutions and ideal solutions using Eqs. (32) and (33). Compute closeness coefficients C_i using Eq. (34). Rank technical solutions in descending order of C_i values.

4 Numerical Calculation Methodology

We conducted an online survey of real estate customers, randomly distributing 300 questionnaires covering 15 preliminary indicators. Based on the collected data and combined with our market research findings, we ultimately selected 5 core CR indicators, as shown in Table 7. For the remaining indicators, we invited real estate industry experts to analyze them. Their assessment concluded that these 10 indicators could serve as DRs corresponding to the 5 selected CRs. Thus, we finalized the DRs as presented in Table 8.

Table 7. Five CR indicators

CRs	CR
CR1	Community real-time price analysis system
CR2	Residential risk assessment assistant
CR3	AI-guided waste sorting
CR4	Personalized lifestyle recommendations
CR5	Green energy-saving management system

This study investigated potential users of smart communities in China through Kano questionnaire surveys. The target respondents were middle-to-high-income individuals aged 25-55 who had engaged in home purchasing or property consulting within the past three years. The sample covered approximately 75% of second-tier and above cities, and about 25% of third-tier cities. Invalid questionnaires containing logical contradictions (e.g., selecting "very like" for both functional and dysfunctional questions) or missing key items were excluded. From 230 collected questionnaires, 205 valid samples were ultimately screened (valid response rate: 89.13%). Particular attention was given to respondents who had experience with digital services such as VR home viewing and smart home technologies, ensuring the sample accurately reflects real demands in digital scenarios. The reliability and validity analyses of the questionnaire are presented in Table 9 and Table 10.

Table 8. Ten DRs

DRs	DRs
DR1	Immersive digital house-viewing service
DR2	Blockchain-based property contract storage
DR3	Smart policy matching and alerts
DR4	Smart home control platform
DR5	Community security monitoring network
DR6	Intelligent parking navigation system
DR7	Health monitoring and care service
DR8	24/7 AI property assistant
DR9	Digital neighbor social platform
DR10	Community asset value analysis tool

Table 9. Reliability test results of Kano questionnaire

	No. of Items	Sample Size	Cronbach's α Coefficient
Positive Items	5	205	0.872
Negative Items	5	205	0.888

Table 10. Validity test results of Kano questionnaire

	KMO	Bartlett's Sphericity Test	
		Approx. Chi-Square	P-Value
Positive Items	0.893	939.481	$<$0.001
Negative Items	0.893	1253.483	$<$0.001

The Kano questionnaire in this study demonstrated high reliability, with Cronbach's α coefficients for both positive and negative items exceeding 0.8, indicating excellent internal consistency and stability of the measurement results. For validity assessment, the KMO values for all items were above 0.7, and Bartlett's test of sphericity showed statistically significant results ($p < 0.001$), which is below the critical threshold of 0.05. These results confirm that our demand survey questionnaire possesses strong construct validity.

Phase I: Kano-Based Requirement Classification Using Interval Type-2 Fuzzy Linguistic Variables.

Step 1: Collecting Customer Fuzzy Linguistic Evaluations of Requirements.

With reference to Table 2, we designed a Kano questionnaire containing five CRs using linguistic terms such as "Very Like", "Must-be". A total of 230 questionnaires were distributed to target real estate customers, and after eliminating invalid responses, 205 valid questionnaires were obtained.

Step 2: Requirement Classification Based on Interval Type-2 Fuzzy Set Distance.

Statistical Results of CR1-CR5 from 205 Respondents (Table 11):

For CR_1, the composite evaluation $\widetilde{U}_1$ was calculated using Eq. (8): $\widetilde{U}_1 = (\widetilde{L} \times 139 + \widetilde{M} \times 44 + \widetilde{N} \times 13 + \widetilde{W} \times 8 + \widetilde{D} \times 1)/205 = ((6.61, 8.09, 8.96, 9.61)(8.03, 8.56, 8.56, 9.18, 0.55))$. Next, the distances between each linguistic term and $\widetilde{U}_i$ *or* $\widetilde{U}_i'$ were calculated: $d\left(\widetilde{L}, \widetilde{U}_i\right) = 0.98, d\left(\widetilde{M}, \widetilde{U}_i\right) = 1.04, d\left(\widetilde{N}, \widetilde{U}_i\right) = 2.96, d\left(\widetilde{W}, \widetilde{U}_i\right) = 5.52, d\left(\widetilde{D}, \widetilde{U}_i\right) = 7.89, d\left(\widetilde{L}, \widetilde{U}_i'\right) = 7.32, d\left(\widetilde{M}, \widetilde{U}_i'\right) = 5.30, d\left(\widetilde{N}, \widetilde{U}_i'\right) = 3.37, d\left(\widetilde{W}, \widetilde{U}_i'\right) = 0.81, d\left(\widetilde{D}, \widetilde{U}_i'\right) = 1.55$. So $\min\left\{d\left(\widetilde{L}, \widetilde{U}_i\right), d\left(\widetilde{M}, \widetilde{U}_i\right), \ldots\right\} = d\left(\widetilde{L}, \widetilde{U}_i\right), \min\left\{d\left(\widetilde{L}, \widetilde{U}_i'\right), d\left(\widetilde{M}, \widetilde{U}_i'\right), \ldots\right\} = d\left(\widetilde{W}, \widetilde{U}_i'\right)$. According to the classification criteria in Table 2, CR_1 belongs to A. Similarly, the categories of the remaining four CRs were determined, with results shown in Table 9.

Table 11. Kano classification of five CR indicators

CRs	F DF	Quality Dimension					Total	Kano Category
		D	W	N	M	L		
CR1	F	1	8	13	44	139	205	Attractive (A)
	DF	101	81	17	5	1	205	
CR2	F	2	5	12	36	150	205	Attractive (A)
	DF	10	48	146	0	1	205	
CR3	F	0	1	6	56	142	205	One-dimensional (O)
	DF	141	34	25	3	2	205	
CR4	F	0	2	3	78	122	205	One-dimensional (O)
	DF	134	56	13	1	1	205	
CR5	F	1	3	6	90	105	205	Must-be (M)
	DF	120	74	10	1	0	205	

Phase II: Determination of Requirement Weights Considering Enterprise Lifecycle.
Step 1: Calculation of Objective Requirement Weights.

According to Eq. (12), the satisfaction coefficients are calculated as: S_1=0.3720, S_2=0.3740, S_3=0.3873, S_4=0.3851, S_5=0.3750. Based on Eq. (13), the dissatisfaction coefficients are: DS_1=-0.2763, DS_2=-0.1096, DS_3=-0.3021, DS_4=-0.3196, DS_5=-0.3174. The normalized target weights are determined using Eq. (14) as follows:

$$\omega_1 = 0.2044, \omega_2 = 0.0818, \omega_3 = 0.2327, \omega_4 = 0.2447, \omega_5 = 0.2367$$

Step 2: Lifecycle-Based Weight Adjustment Assessment.

The enterprise's current development stage (start-up, growth, maturity, or decline) is identified based on operational conditions. The necessity for weight adjustment across requirement categories is evaluated according to stage-specific priority rules.

Step 3: Computation of Normalized Requirement Weights.

For weights requiring adjustment, the reference points are determined based on the regret theory parameters in Table 5, and the adjusted weights ω_i' are calculated using Eq. (17). Finally, the normalized weights μ_i are obtained through Eq. (18).

Based on the previously calculated values, the data for Table 12 can be obtained as follows:

Table 12. The adjusted weights ω_i' and the normalized weights μ_i

	ω_1'	ω_2'	ω_3'	ω_4'	ω_5'	μ_1	μ_2	μ_3	μ_4	μ_5
Start-up	0.1491	0	0.2248	0.2441	0.2360	0.1744	0	0.2631	0.2856	0.2769
Growth	0.1590	0	0.2327	0.2552	0.2363	1.1800	0	0.2635	0.2890	0.2675
Maturity	0.2922	0.0818	0.0899	0.0730	0.0839	0.4715	0.1320	0.1434	0.1178	0.1353
Decline	0.1437	0	0.2241	0.2457	0.2367	0.1690	0	0.2636	0.2890	0.2784

Phase III: Prioritization of Technical Solutions Based on Regret-GETOPSIS.
Step 1: Construction of Standardized Interval Type-2 Fuzzy Relation Matrix.

This study invited four senior experts (labeled D_1, D_2, D_3, and D_4 respectively) with over 10 years of experience in the real estate industry to evaluate the correlation between 5 CRs and 10 DRs using interval type-2 fuzzy linguistic term sets. The evaluation employed the following linguistic terms: EH, VH, H, M, L, VL, EL. The specific evaluations are shown in Table 13, Table 14, Table 15, and Table 16.

Table 13. Evaluation matrix for expert D_1

		DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10
D1	CR1	VH	M	EH	L	VL	EL	M	H	VL	EH
	CR2	M	EH	VH	EL	L	M	H	VH	L	EH
	CR3	L	VL	EL	H	EH	VH	M	L	H	VL
	CR4	EH	H	M	VH	H	M	L	EH	VH	M
	CR5	VL	L	VL	EH	VH	H	EH	M	H	L

Table 14. Evaluation matrix for expert D_2

		DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10
	CR1	H	M	VH	VL	EL	L	M	VH	EL	EH
	CR2	L	EH	EH	EL	M	H	VH	EH	M	VH
D2	CR3	VL	EL	L	VH	EH	EH	M	L	H	EL
	CR4	VH	EH	H	H	M	L	EL	H	VH	H
	CR5	EL	M	EL	EH	VH	VH	EH	M	M	VL

Table 15. Evaluation matrix for expert D_3

		DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10
	CR1	H	M	EH	L	VL	EL	M	VH	VL	EH
	CR2	M	EH	VH	EL	L	M	H	EH	L	VH
D3	CR3	VL	EL	L	H	EH	VH	M	L	H	VL
	CR4	EH	VH	M	VH	H	M	L	EH	VH	M
	CR5	EL	L	VL	EH	VH	H	EH	M	H	L

Table 16. Evaluation matrix for expert D_4

		DR1	DR2	DR3	DR4	DR5	DR6	DR7	DR8	DR9	DR10
	CR1	M	L	EH	VL	EL	EL	H	M	EL	VH
	CR2	L	M	VH	EL	H	L	VH	H	EL	H
D4	CR3	H	EL	M	EH	VH	H	EH	M	VH	L
	CR4	VH	M	H	M	M	VL	L	VH	M	L
	CR5	EH	VL	L	VH	EH	VH	H	H	EH	VL

Step 2: Aggregate Expert Evaluations and Convert to Interval Grey Numbers.
Aggregate individual matrices using the interval type-2 fuzzy weighted average operator Eq. (20). Determine expert weights through the improved entropy weight method Eq. (21). Convert the aggregated results into interval grey numbers $\otimes r_{ij}$ using Eq. (22).

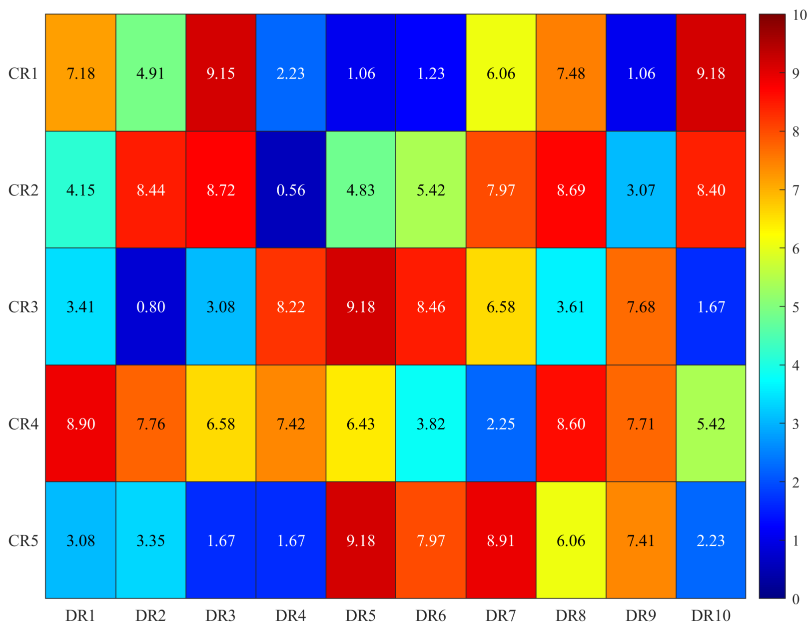

Figure 10. CR-DR relationship matrix

Based on Table 13, Table 14, Table 15, and Table 16, we construct the correlation matrix $\widetilde{A}^k = (\widetilde{a}_{ij}^k)_{m\times n}$ for each expert dk. Following Eqs. (20) and (21), we obtain $\widetilde{r}_{ij}$ (for ease of representation, we use the average of the upper and lower bounds to denote $\widetilde{r}_{ij}$), with Figure 10 displaying a heatmap of the aggregated centroid values. The expert weights μ_k are determined via the improved entropy weight method: μ_1=0.2244, μ_2=0.2835, μ_3=0.2352, μ_4=0.2568. Box I (Figure 11) visually presents the experts' evaluations of CRs through line charts, demonstrating the correlation levels between CRs and DRs.

$$\tilde{r}_{ij} = \begin{bmatrix} 7.1760 & 4.9076 & 9.1495 & 2.2327 & 1.0582 & 1.2306 & 6.0595 & 7.4799 & 1.0582 & 9.1758 \\ 4.1512 & 8.4437 & 8.7230 & 0.5600 & 4.8333 & 5.4233 & 7.9691 & 8.6897 & 3.0741 & 8.3997 \\ 3.4112 & 0.8032 & 3.0791 & 8.2220 & 9.1788 & 8.4579 & 6.5775 & 3.6099 & 7.6764 & 1.6654 \\ 8.8965 & 7.7592 & 6.5752 & 7.4189 & 6.4286 & 3.8222 & 2.2544 & 8.6038 & 7.7112 & 5.4233 \\ 3.0804 & 3.3524 & 1.6654 & 1.6654 & 9.1758 & 7.9697 & 8.9107 & 6.0595 & 7.4136 & 2.2327 \end{bmatrix}$$

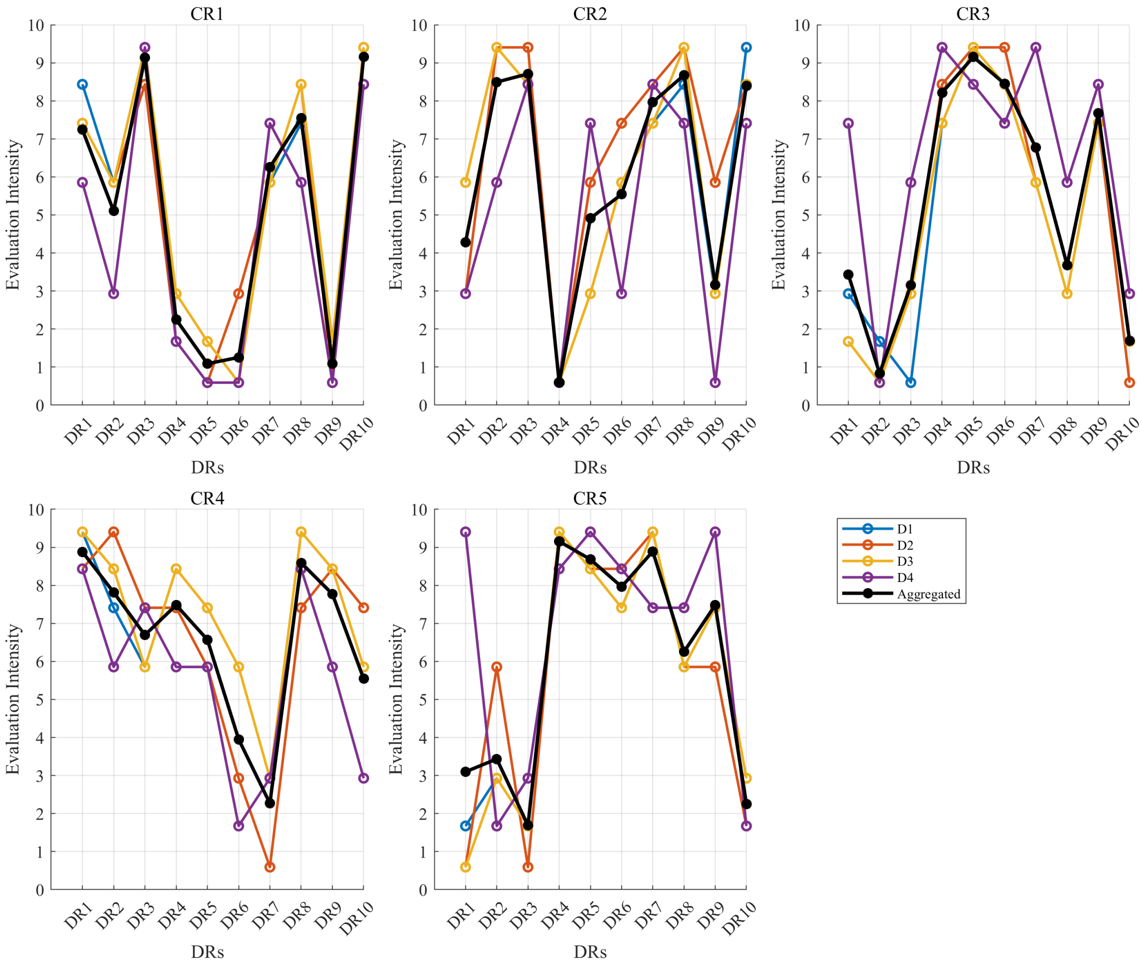

Figure 11. Box I: Multi-dimensional evaluation intensity comparison of DRs

Step 3: Determine Comprehensive Weights Integrating Grey Entropy and Lifecycle Factors.

We invited experts to score the importance of CRs across four lifecycle stages, with results normalized to obtain the weight distribution shown in Table 17.

Based on Eqs. (22) and (26), we calculate the integrated weights for CRs across four lifecycle stages as follows (Table 18):

Step 4: Construct Behavioral Decision Matrix Incorporating Regret Theory.

Determine positive and negative ideal solutions (PIS and NIS) using Eqs. (28)-(29). Calculate perceived utility values v_{ij}, including regret/rejoice effects, through Eqs. (27), (30) and (31). The perceived utility matrices for all four lifecycle stages are presented in Box II, with Heatmap 11 (Figure 12) providing a visual representation of the stage-specific utility values v_{ij} calculated.

Table 17. Normalized weights of CRs across lifecycle stages

	w_1^{LC}	w_2^{LC}	w_3^{LC}	w_4^{LC}	w_5^{LC}	w_6^{LC}	w_7^{LC}	w_8^{LC}	w_9^{LC}	w_{10}^{LC}
Start-up	0.0870	0.1043	0.1304	0.0783	0.1478	0.0957	0.1391	0.0696	0.0609	0.0870
Growth	0.1231	0.1077	0.0923	0.1000	0.0846	0.0923	0.0769	0.1154	0.1077	0.1000
Maturity	0.1032	0.0873	0.0794	0.1190	0.0794	0.1111	0.0952	0.1032	0.0952	0.1270
Decline	0.0753	0.0860	0.1505	0.0645	0.1720	0.0968	0.1613	0.0538	0.0645	0.0753

Table 18. The integrated weights

	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}
Start-up	0.0749	0.1182	0.1185	0.1360	0.1279	0.1000	0.0877	0.0459	0.0850	0.1058
Growth	0.0884	0.1191	0.0989	0.1524	0.0960	0.0974	0.0646	0.0586	0.1121	0.1125
Maturity	0.0805	0.1067	0.0912	0.1654	0.0925	0.1063	0.0715	0.0551	0.1048	0.1261
Decline	0.0706	0.1087	0.1290	0.1251	0.1398	0.1019	0.0957	0.0409	0.0886	0.0997

$$v_{ij} = \begin{bmatrix} 6.5854 & 4.8696 & 7.9677 & 2.5554 & 2.4173 & 1.2233 & 5.7472 & 6.8080 & 1.3405 & 7.9924 \\ 4.2653 & 7.4830 & 7.4764 & 7.6814 & 0.4031 & 5.2744 & 7.1431 & 7.6594 & 3.3729 & 7.4541 \\ 3.6360 & 0.8935 & 3.2788 & 7.3318 & 7.9849 & 7.4932 & 6.1350 & 3.3552 & 6.9514 & 1.9461 \\ 7.8001 & 7.0002 & 6.1304 & 6.7627 & 6.0135 & 3.9790 & 2.4907 & 7.5997 & 6.9761 & 5.2790 \\ 3.3407 & 3.5695 & 1.8446 & 1.9720 & 1.7981 & 7.9912 & 7.1436 & 7.8124 & 5.9055 & 2.5348 \end{bmatrix}$$

Perceived Utility Matrix for Start-up Stage

$$v_{ij} = \begin{bmatrix} 6.5750 & 4.8675 & 7.9736 & 2.5196 & 2.5389 & 1.2331 & 5.7708 & 6.7966 & 1.2328 & 7.9905 \\ 4.2345 & 7.4824 & 7.4839 & 7.6780 & 0.6030 & 5.2762 & 7.1553 & 7.6518 & 3.3253 & 7.4516 \\ 3.5954 & 0.8831 & 3.3303 & 7.3278 & 7.9948 & 7.4938 & 6.1547 & 3.2989 & 6.9424 & 1.9171 \\ 7.7943 & 6.9995 & 6.1448 & 6.7573 & 6.0392 & 3.9823 & 2.5881 & 7.5920 & 6.9671 & 5.2721 \\ 3.2946 & 3.5658 & 1.9349 & 1.9269 & 1.9512 & 7.9917 & 7.1557 & 7.8054 & 5.8906 & 2.5118 \end{bmatrix}$$

Perceived Utility Matrix for Growth Stage

$$v_{ij} = \begin{bmatrix} 6.5809 & 4.8796 & 7.9754 & 2.4861 & 2.5478 & 1.1772 & 5.7643 & 6.7998 & 1.2630 & 7.9863 \\ 4.2519 & 7.4859 & 7.4863 & 7.6748 & 0.6210 & 5.2659 & 7.1519 & 7.6540 & 3.3387 & 7.4462 \\ 3.6184 & 0.9439 & 3.3462 & 7.3240 & 7.9956 & 7.4902 & 6.1493 & 3.3148 & 6.9449 & 1.8524 \\ 7.7976 & 7.0039 & 6.1492 & 6.7523 & 6.0410 & 3.9637 & 2.5614 & 7.5941 & 6.9697 & 5.2566 \\ 3.3207 & 3.5873 & 1.9629 & 1.8847 & 1.9624 & 7.9889 & 7.1524 & 7.8074 & 5.8948 & 2.4604 \end{bmatrix}$$

Perceived Utility Matrix for Maturity Stage

$$v_{ij} = \begin{bmatrix} 6.5885 & 4.8803 & 7.9642 & 2.5768 & 2.3631 & 1.2200 & 5.7376 & 6.8116 & 1.3328 & 7.9941 \\ 4.2745 & 7.4861 & 7.4720 & 7.6834 & 0.3376 & 5.2738 & 7.1382 & 7.6617 & 3.3695 & 7.4562 \\ 3.6481 & 0.9476 & 3.2488 & 7.3343 & 7.9805 & 7.4930 & 6.1270 & 3.3727 & 6.9507 & 1.9711 \\ 7.8018 & 7.0042 & 6.1221 & 6.7659 & 6.0021 & 3.9780 & 2.4512 & 7.6021 & 6.9754 & 5.2850 \\ 3.3545 & 3.5886 & 1.7919 & 1.9989 & 1.7298 & 7.9910 & 7.1386 & 7.8146 & 5.9045 & 2.5547 \end{bmatrix}$$

Perceived Utility Matrix for Decline Stage

Box II: Perceived utility matrices across enterprise lifecycle stages

Calculate distances D_i^+ and D_i^- between solutions and ideal solutions using Eqs. (32) and (33). Compute closeness coefficients C_i using Eq. (34). Rank technical solutions in descending order of C_i values (Table 19).

According to Table 19, we can observe that DR5 has the highest C_i value in the start-up stage, while DR2 shows the highest C_i value in the growth stage. In the maturity stage, DR10 achieves the maximum C_i value, and in the decline stage, DR5 again demonstrates the highest C_i value, with corresponding values of 0.5416, 0.5270, 0.5296, and 0.5481. Table 20 presents the comprehensive ranking of all DRs across the four lifecycle stages.

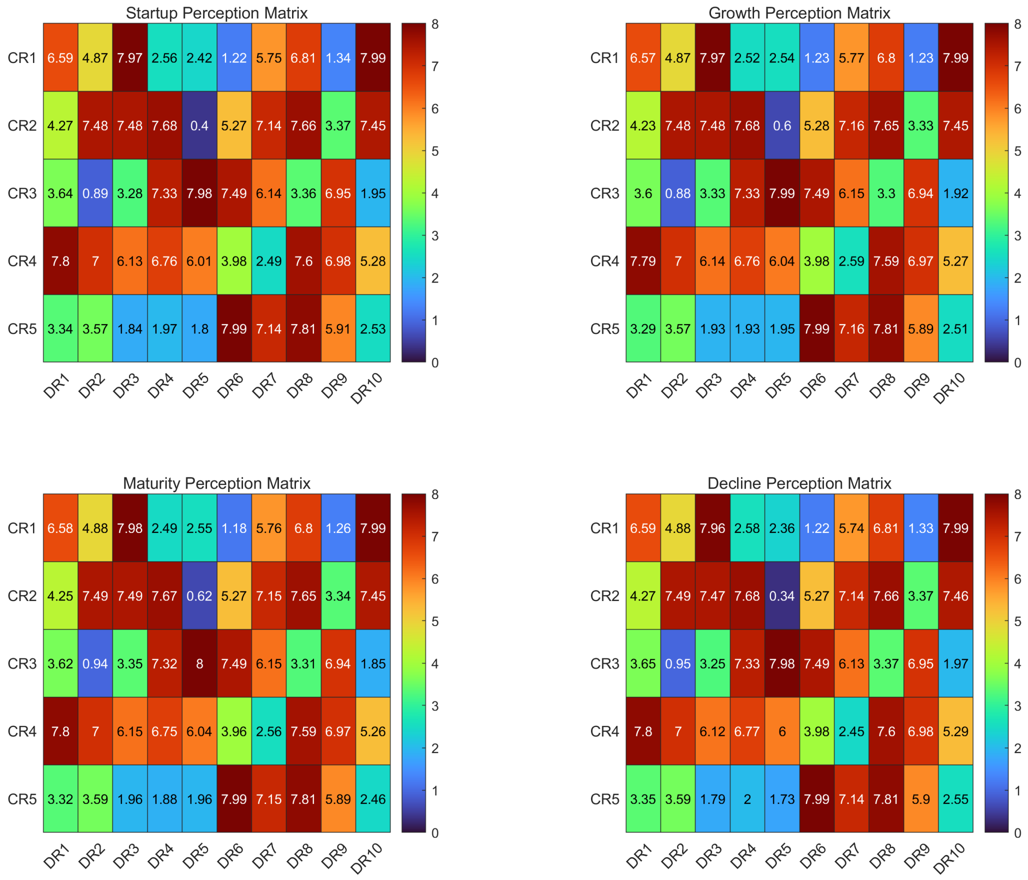

Figure 12. Heatmap of perceived utility matrices across lifecycle stages

Table 19. Closeness coefficient C_i values

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}
Start-up	0.5168	0.5261	0.5297	0.5164	0.5416	0.5236	0.5253	0.5107	0.5132	0.5199
Growth	0.5245	0.5270	0.5206	0.5211	0.5240	0.5227	0.5134	0.5183	0.5239	0.5230
Maturity	0.5202	0.5217	0.5176	0.5253	0.5225	0.5275	0.5168	0.5163	0.521	0.5296
Decline	0.5144	0.5214	0.5346	0.5134	0.5481	0.5238	0.5298	0.5082	0.5140	0.5171

Table 20. Comprehensive ranking of DRs across lifecycle stages

	Overall Ranking
Start-up	*DR5>DR3>DR2>DR7>DR6>DR10>DR1>DR4>DR9>DR8*
Growth	*DR2>DR1>DR5>DR9>DR10>DR6>DR4>DR3>DR8>DR7*
Maturity	*DR10>DR6>DR4>DR5>DR2>DR9>DR1>DR3>DR7>DR8*
Decline	*DR5>DR3>DR7>DR6>DR2>DR10>DR1>DR9>DR4>DR8*

To more intuitively demonstrate the evolution of DR priorities across enterprise lifecycle stages, Figure 13 presents a horizontal comparison of DR rankings distribution across the four stages, while Figure 14 uses line charts to compare the closeness coefficient (C_i) values of different DRs throughout the lifecycle. These two figures clearly reveal the varying importance levels of different DRs across the four stages.

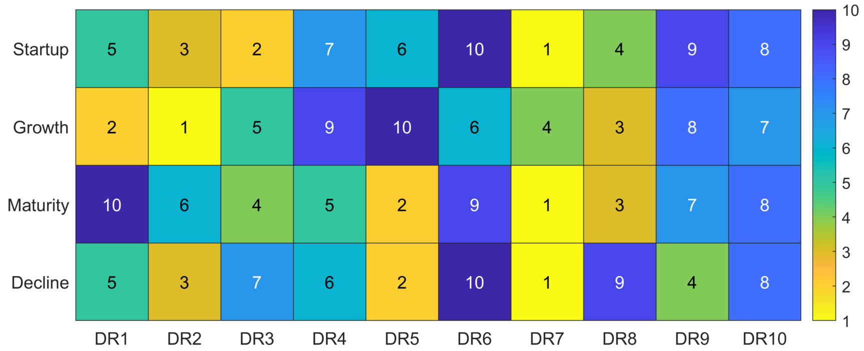

Figure 13. DR rankings across lifecycle stages

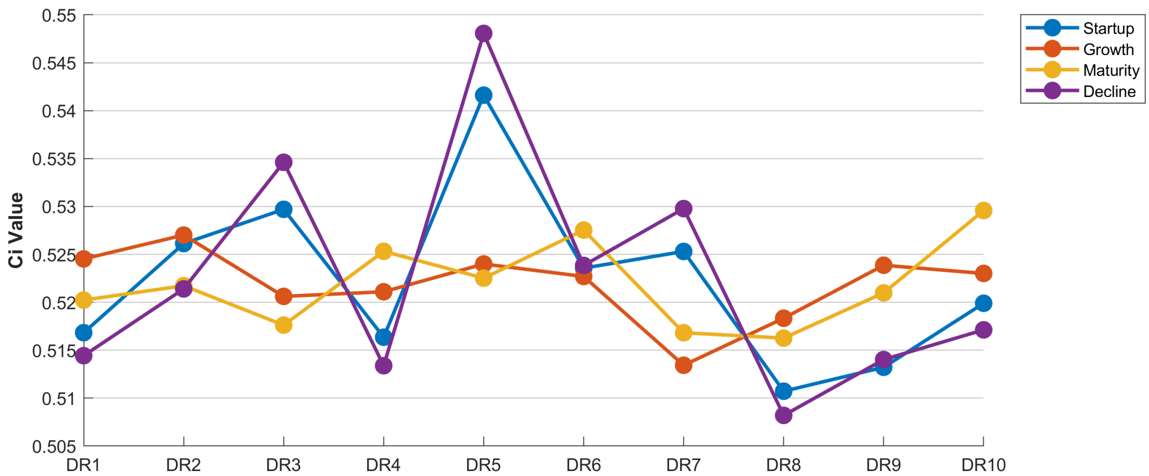

Figure 14. Closeness coefficient comparison

5 Conclusions

This study focuses on the dynamic changes in residents' demands during the digital transformation of smart communities and the decision-making challenges in service optimization. By integrating the Interval Type-2 Fuzzy Kano Model, Regret Theory, and the GETOPSIS method, we have constructed an innovative QFD framework, providing new insights for improving resident satisfaction and facilitating smart community upgrades in the property industry. The model introduces an enterprise lifecycle adjustment mechanism to achieve dynamic matching between technology priorities and strategic objectives, effectively overcoming the limitations of traditional QFD in handling semantic ambiguity and behavioral biases. Empirical analysis shows that startup enterprises pay greater attention to basic functions such as community intelligent security systems, while mature enterprises tend to invest more in value-added services like green energy efficiency optimization. The study's samples mainly come from China's first- and second-tier cities (accounting for 75%) and some third-tier cities (25%), covering regions with different economic development levels. Although the sample has certain representativeness in terms of regional distribution, it should be noted that:

1. The sample size from third-tier cities is relatively small, and their technology adoption preferences may be influenced by local policies or consumption habits. Follow-up studies could include more targeted investigations of lower-tier markets.

2. The empirical results of the framework in the Chinese market should be cautiously generalized to regions with different cultural backgrounds. It is recommended to adjust the model parameters based on local data.

Theoretical breakthroughs are manifested in three dimensions: First, the framework establishes a realistic analytical foundation for QFD by synergistically integrating higher-order uncertainty modeling of linguistic variables with behavioral decision theory. Second, the regret theory-based dynamic weight adjustment mechanism elucidates the intrinsic patterns of technology adoption preferences across enterprise lifecycle stages. Third, the dual-dimensional ideal solution reference system enhances the GETOPSIS method, effectively resolving reliability issues in technical solution prioritization under uncertainty. These innovations provide new methodological support for product development research in complex decision-making environments.

In practical terms, the framework developed in this study provides the property industry with an actionable roadmap for adopting smart technologies. The survey results reveal that residential decision-support demands exhibit prominent attractive attributes, while lifestyle optimization demands - which offer clear guidance for enterprise resource allocation - demonstrate expected attributes. Particularly noteworthy is the model's identification of technology prioritization patterns that evolve with corporate lifecycles, enabling enterprises to avoid common strategic pitfalls.

This study, although it has achieved the above results, still has several issues that are worth exploring in depth. First, more industry data are needed to verify the universality of the model parameters in the paper; moreover, we found that the current stage life cycle division is relatively static, and the future dynamic adjustment can be introduced into the instant operation data; finally, how to apply emerging technologies such as blockchain in real-time collection and updating of customer demand data is also an important direction for the framework's practicality improvement. These extended researches can not only make the existing theoretical system more perfect, but also enhance the resilience of the model in case of rapid changes in the market environment.

Taken together, the integrated framework proposed in this paper provides a theoretical cross-fertilization of both theoretical and real-world value solutions for technology adoption decision-making in uncertainty environments, and the research idea combines customer demand analysis, behavioral decision-making mechanisms and corporate strategy dynamics, which will provide continuous theoretical support and methodological guidance for the refinement and upgrading of smart properties. In terms of model automation and cross-cultural applicability, future research can continue to deepen, thus contributing to the theory of quality function unfolding in the era of the digital economy.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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