Identifying and Classifying Residents' demand for Smart Community Development: An Empirical Analysis from China

Yujia Shan[1] and Tiantian Gu[1]

[1] School of Mechanics and Civil Engineering, China University of Mining and Technology, Xuzhou, China

ts24030295a31tm@cumt.edu.cn, 6072@cumt.edu.cn

Abstract

Smart community development is pivotal for modernizing grassroots governance. However, few studies have established a systematic classification model for residents' multi-dimensional needs. To fill this research gap, this paper constructs a comprehensive demand analysis framework covering three core dimensions: community safety, livability services and community governance. Based on the survey data of 191 valid samples from 5 typical smart communities in Huizhou, this study uses hierarchical clustering and K-means clustering to identify and classify residents' demand types. The results divide residents into four clusters: weak service-oriented demand group, safety and governance priority demand group, strong service demand group and comprehensive demand group. This taxonomy framework offers a replicable methodology for smart community planning with diverse resident demand priorities. Additionally, grounded in empirical analysis of Huizhou, China, it provides smart community development strategies for the Chinese context to enhance smart community development efficacy.

Keywords –

Smart community; Residents' demand; Community governance; Cluster analysis

1 Introduction

Smart community development plays a pivotal role in driving sustainable urbanization, serving as the operational backbone of broader smart city frameworks [1]. Generally, such initiatives adopt digital technologies to enhance urban quality of life, operational efficiency, and governance structures [2]. During public health emergencies, smart communities also showed obvious advantages in rapid early warning, closed management and resource allocation [3]. Yet the effectiveness of these efforts hinges on a systematic grasp of what residents actually need [4]. Given that residents hold diverse and often competing priorities, failing to quantitatively capture this demand landscape risks misallocated investments, poor uptake, and ultimately project failure [5]. Therefore, a deep understanding of residents' needs is essential to shift the focus of smart community development from a technology-first approach to one that puts people at the center [6].

In existing literature, the governance functions of smart communities have been extensively analyzed, but discussions on the actual demands of residents remain fragmented. For instance, the roles of various stakeholders have been clarified, and the development orientations of community property service enterprises, government agencies, and other participants have been further analyzed in the process [7]. From the property management side, researchers have examined how firms adapt their operations and business models under digital transformation [4], while public administration scholars have focused on policy execution and governance outcomes [8, 9]. However, in existing research, residents typically occupy a passive position. Consequently, another strand of literature has concentrated on residents' needs and experiences to evaluate specific smart community functions and adjust development strategies. Scholars have investigated satisfaction and supply-demand matching in specific functional domains, including older adult care services [10], residential energy scheduling [11], and water demand management [12]. Additionally, few studies have explored residents' demands for smart community development [13]. Taken together, this work points to two related shortcomings. On the one hand, most studies examine isolated service functions rather than constructing a comprehensive demand indicator framework. On the other hand, rigorous quantitative tools for mapping multi-dimensional demand profiles across resident groups remain absent.

To address these gaps, this study developed a resident demand indicator system covering three dimensions of smart community development, then built a classification model by combining hierarchical clustering with K-means analysis. Drawing on 191 valid survey responses, the approach identifies empirically grounded demand clusters among residents. Theoretically, this research filled the theoretical gap of lacking a systematic indicator system that integrates multi-dimensional residents' demands. It also introduces a data-driven taxonomy that moves the field beyond isolated functional analyses toward an integrated view of demand patterns. Practically, suggestions were designed for the case communities directly and offered a transferable reference for smart community projects with comparable demand profiles, supporting more effective project implementation in similar contexts.

2 Methodology

2.1 Establishment of the residents' demand indicator system

The selection of resident demand indicators drew on two complementary theoretical foundations: Maslow's Hierarchy of Needs and the Kano Model [14]. These frameworks were chosen because their respective strengths align well with the dual task of ordering and categorizing demands in a smart community context [15]. Maslow's hierarchy traces how human needs progress from basic survival concerns to higher-order aspirations [16], while the Kano Model offers a mechanism for classifying demands based on their impact on satisfaction [17]. Used in combination, the two models support a structured analysis of resident demands that spans from foundational safety concerns to active participation in community governance.

The resulting integrated indicator system (see Figure 1) organizes resident demands into three core dimensions. The first, Community Safety, corresponds to Maslow's safety needs level and captures residents' baseline expectations for protecting life and property [18-22]. Under the Kano Model, these function as Must-be Quality attributes: their absence triggers strong dissatisfaction, yet their presence alone does not generate positive responses. The second dimension, Community Services, maps onto the love and belongingness and esteem needs in Maslow's framework, covering services that raise living standards and reinforce social identity [23-27]. The Kano Model treats these largely as One-dimensional Quality demands, where satisfaction climbs in step with service performance. The third dimension, Community Governance, reflects Maslow's self-actualization level and concerns residents' involvement in community decision-making processes [8, 28-30]. In Kano terms, these are Attractive Quality attributes. Their presence can substantially lift satisfaction, but their absence does not provoke dissatisfaction.

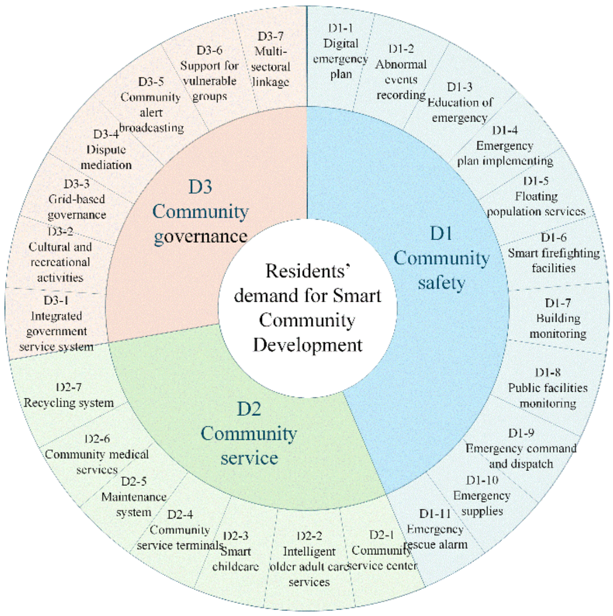

Figure 1. The residents' demand indicator system

Demand indicator selection relied on an expert scoring exercise drawing on 38 valid responses from a panel of 50 invited participants, spanning both academic researchers and seasoned practitioners. The expert panel composition is shown in Table 1. This process resulted in the final demand indicator system, consisting of 3 primary and 25 secondary indicators, as summarized in Figure 1.

Table 1. Information of the 38 experts surveyed

Variable	Items	Percentage (%)
Gender	Male	47.37
	Female	52.63
Years of Experience	Over 5 years	18.42
	4-5 years	31.58
	1-3 years	23.68
	Within one year	26.32
Professional Field	Academia	39.47
	Enterprise	60.53

2.2 Development of the residents' demand classification model

Building on this indicator system, a demand classification model was constructed by combining hierarchical cluster analysis (HCA) with k-means clustering to categorize resident demand profiles in a systematic way. The two methods were paired for their complementary roles. HCA was used first to determine the appropriate number of clusters by interrogating the underlying data structure, after which k-means clustering was applied to partition samples into stable, wellseparated groups [31]. Cluster analysis is a multivariate statistical technique that groups samples according to similarity, making it well suited to uncovering typologies within complex resident demand data [32].

(a). Calculation of initial distances

$$d_{ij} = \sum_{k=1}^{m}(x_{it} - x_{jt})^2 \tag{1}$$

$$S = \sum_{i=1}^{n}(x_{i1} - \frac{\sum_{i=1}^{n} x_{i1}}{n})^2 + \ldots + \sum_{i=1}^{n}(x_{im} - \frac{\sum_{i=1}^{n} x_{im}}{n})^2 \tag{2}$$

where x_{it} and x_{jt} represent the data of the t-th indicator in the i-th sample and j-th sample, respectively. d_{ij} denotes the distance between the i-th sample and the j-th sample in terms of three dimensions. S denotes the sum of squared deviations.

(b). Cluster merging based on minimum distance

If clusters p and q are merged into a new cluster l, the sum of squared deviations of cluster l was:

$$S_l = S_p + S_q + \frac{n_p n_q}{n_p + n_q}(\overline{x_p} - \overline{x_q})^2 \tag{3}$$

$$d_{pq} = \triangle S_{pq} = \frac{n_p n_q}{n_p + n_q}(\overline{x_p} - \overline{x_q})^2 \tag{4}$$

The distance between the new cluster l and any arbitrary cluster r was calculated using the following formula:

$$d_{lr} = \frac{n_p + n_r}{n_l + n_r} d_{pr} + \frac{n_q + n_r}{n_l + n_r} d_{qr} - \frac{n_r}{n_l + n_r} d_{pq} \tag{5}$$

where p and q contain n_p and n_q samples and their corresponding sums of squared deviations are denoted as S_p and S_q.

(c). Determination of the optimal number of clusters (k).

Step (b) is repeated iteratively, merging the two nearest clusters at each pass until all samples converge into a single cluster. This process generates agglomeration coefficients for successive cluster solutions, and the relationship between these coefficients and the number of clusters is then examined to identify the optimal cluster count (k).

(d). Calculation of the new distance matrix

K-means clustering was applied with the optimal cluster number (k=4) determined from the hierarchical clustering analysis. The algorithm employed k-means++ initialization, which selects initial cluster centers based on distance. With k centers established ($c_{j'}$, where j'=1, 2, …, k), the Euclidean distance $D(x_i, c_{j'})$ between each sample and every center was computed, and the resulting distance matrix was constructed as follows:

$$D = (d_{ij}) = \begin{bmatrix} d_{11}, & d_{12}, & \ldots, & d_{1k} \\ d_{21}, & d_{22}, & \ldots & d_{2k} \\ \ldots & \ldots & \ldots & \ldots. \\ d_{n1}, & d_{n2}, & \ldots & d_{nk} \end{bmatrix} \tag{6}$$

Each sample is then assigned to the cluster j' with the min $D(x_i, c_{j'})$, which satisfied: $D(x_i, c_{j'}) = \min\{D(x_i, c_{j'})\}$ (i=1, 2, …, n; j'= 1, 2, …, k), the sample belongs to the j'-th cluster.

(f). Calculation of the k new cluster centers:

$$C_{j'}(I+1) = \frac{1}{n_{j'}} \sum_{x' \in C_{j'}} x' \tag{7}$$

Where $n_{j'}$ denotes the number of samples in cluster $C_{j'}$; x' denotes the samples classified into cluster $C_{j'}$.

This process continued until cluster assignments no longer changed and the sum of squared errors reached convergence. The procedure yielded k distinct clusters, each carrying a characteristic demand profile across the three core dimensions. Together, these clusters constitute an empirically grounded typology of smart community development patterns, organized around the underlying structure of resident demand.

3 Study area and data collection

3.1 Study area

Huizhou, located in Guangdong Province, China, was among the first batch of 20 pilot smart cities approved by the Chinese government in 2013. In the field of smart community, the Huizhou Municipal Government has been committed to advancing community digital governance, promoting age-friendly and barrier-free renovations, constructing community digital facilities, and establishing information management platforms. These persistent efforts have yielded remarkable achievements in optimizing community services and enhancing governance efficiency. Given that Huizhou is a representative city with a long-standing development history, rich practical experience, and outstanding accomplishments in China's smart community development, it serves as a typical study area for analyzing the residents' demand for smart community development.

To ensure the validity and representativeness of the sample, five communities with smart community outcomes were selected as the study cases, including

Banzhangling, Qingxi, Siqian, Tangjing and Tongxin. These communities all have smart upgrades in community safety and governance dimensions, and are equipped with functions such as resident demand management, grid-based governance, management of the floating population and intelligent patrol systems. Additionally, the five communities have integrated community service functions, such as home-based eldercare, smart healthcare services, intelligent charging facilities and community service centers. This selection ensures that the sample represents actual smart community development while capturing variation in residents' demand.

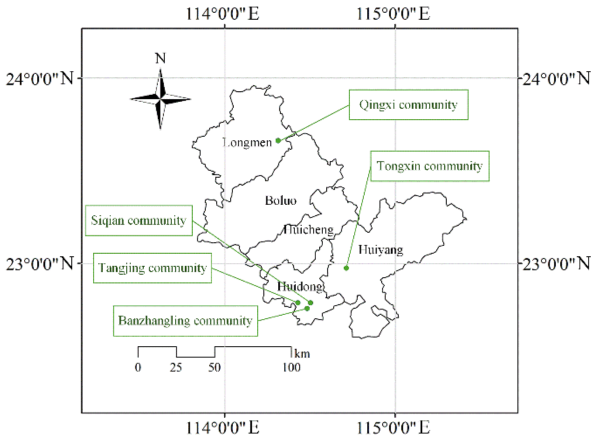

Figure 2. Study area

3.2 Data collection

Survey data were collected through 'Wenjuanxing', a professional online platform for questionnaire distribution and data collection. A total of 230 questionnaires were sent to residents across the 5 selected smart communities (see Figure 2), and after standard validation procedures, 191 responses were retained as complete and usable, corresponding to a response rate of 83.04%.

4 Results

4.1 Quantification of residents' demands for smart community development

Based on the 191 valid resident questionnaires, the demand of residents for smart community development was assessed. The results revealed significant disparities in demand level across the three dimensions of community safety, community services, and community governance. Overall, residents demonstrated their highest prioritization for community safety (avg. 3.85), followed by community services (avg. 3.77) and community governance (avg. 3.66), revealing that current security concerns take precedence over broader issues of service quality and governance participation. A detailed examination of secondary indicators provides further insights. The average demand scores for these indicators are summarized in Figure 3. Within community safety, residents exhibited particularly strong demand for D1-1 (Digital emergency plan) and D1-3 (Propaganda and education of emergency safety), while showing relatively lower demand for D1-8 (Public facilities monitoring). In community services, D2-6 (Community medical services) received the highest average score, while D2-3 (Smart childcare) scored the lowest. The seven indicators of community governance dimension all showed relatively low demand scores, with D3-1 (Integrated government service system) and D3-7 (Multi-sectoral linkage) recording the lowest scores. These patterns indicated that most residents place greater emphasis on safety outcomes in smart community development, particularly in emergency preparedness and safety education, while expressing lower demand for infrastructure monitoring, smart childcare, and community governance functions.

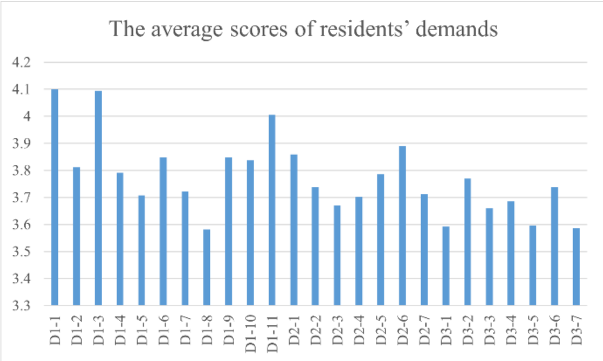

Figure 3. The average demand scores for all indicators

4.2 Clusters of residents' demands for smart community development

To further identify the diverse patterns of residents' demands, a classification model was employed on the demand scores of the 191 respondents. The dataset demonstrated high reliability and validity, with a Cronbach's Alpha of 0.833 and a KMO measure of 0.83 (Bartlett's test $p<0.001$).

The optimal cluster number was subsequently determined using hierarchical clustering with Ward's method. Based on the agglomeration schedule, the optimal cluster number was identified at $k = 4$. Specifically, the growth rate of the agglomeration coefficient exhibited a marked deceleration after the cluster number reached 4, decreasing from 21.07% ($k = 3$ to $k = 4$) to 7.65% ($k = 4$ to $k = 5$). This indicates that more clusters would gradually diminish the differentiation between resident demand clusters, thus validating k = 4 as the optimal number. Following this, resident demands were partitioned into four clusters using k-means clustering. The clustering process regarded as convergent when the relative change in cluster centers fell below the tolerance threshold of 10^{-4}, indicating that the resulting cluster assignments had stabilized.

The final cluster centers resulting from this analysis are illustrated in Figure 4. The result showed a Silhouette Score of 0.283 and a Calinski-Harabasz index of 106.1, supporting the validity of the cluster structure. Cluster 1 comprised 14 respondents, Cluster 2 comprised 55, Cluster 3 comprised 56, and Cluster 4 comprised 66.

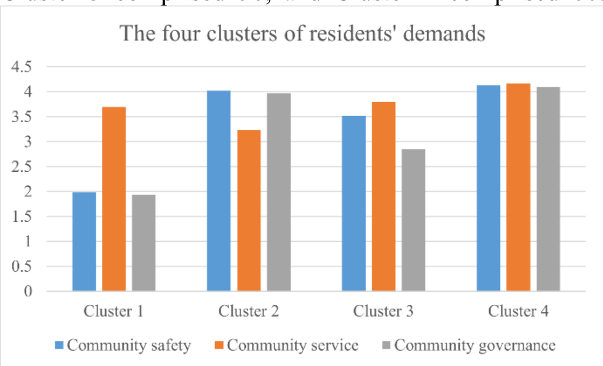

Figure 4. The four clusters of residents' demands

The four clusters showed markedly different demand profiles. Cluster 1 recorded uniformly low scores across all three dimensions (community safety, community services, and community governance). Cluster 2 stand out for its low community services demand, alongside high scores in safety and governance. Cluster 3 posted a high average in community services while falling below average in both safety and governance. Cluster 4 exceeded the overall average across all three dimensions, reflecting a broadly elevated demand profile.

Drawing on these profiles, the four clusters were defined as follows. Cluster 1 (weak service-focused demand) recorded low scores across all three dimensions with a marginal tilt toward basic livability, accounting for the smallest subset of only 14 respondents. Cluster 2 (prioritized safety and governance demand) concentrated demand on safety and governance while showing limited interest in community services, a pattern consistent with the sample-level finding that community safety achieved the highest overall average score. Cluster 3 (strong community services demand) was marked by elevated demand for community services, particularly medical services, alongside lower scores in safety and governance. Cluster 4 (comprehensive demand across all dimensions) maintained high scores across all three domains and represents the largest group at 66 respondents. This empirically grounded grouping captures the demand heterogeneity among residents and offers a practical foundation for formulating differentiated smart community development strategies.

4.3 Strategies to Satisfy residents' Demands for the Smart Community Development

Drawing from quantified demand profiles that identify four distinct resident clusters, effective smart community development requires moving beyond one-size-fits-all solutions toward tailored strategies that address specific resident needs.

For the communities where the residents' demand fell under cluster 1, priority could be given to establish fundamental smart community capabilities that improve daily living. The initial stage focuses on developing digital infrastructure for daily services to bring convenience to residents' everyday lives, including basic medical care, elderly care, community service centers, and other essential services [33]. This objective can be accomplished through the deployment of professional operators, who can enter into performance-based contracts with explicit service-level agreements. These contracts ensure that residents receive reliable and high-quality smart services [34].

For Cluster 2 communities, where residents demonstrate strong demand for safety and governance, targeted public investment is required to address functional deficiencies that affect resident security and civic participation. Emphasis could be placed on establishing centralised community data platforms to improve the efficiency of community safety response and enable active resident participation in governance [35]. Financial sustainability could be supported through instruments such as municipal bonds earmarked for smart city projects [36]. In addition, parallel administrative reforms clarifying jurisdictional boundaries and streamlining service workflows are essential to build digital governance platforms [37], and the clear and streamlined service workflows can enhance public willingness to participate in community governance and improve service experiences.

For communities characterized by Cluster 3, where service demand is high but safety and governance expectations are comparatively low, policy efforts should target market-driven innovation in sectors that directly shape residents' daily lives. A regulatory environment that incentivises private investment in domains residents prioritise, such as community healthcare and smart recycling, can help to achieve this [38]. At the same time, minimum service standards for smart community security [39] and operational oversight arrangements [40] should be put in place to guard against the under-provision of safety and governance functions.

Finally, for communities exhibiting the demand profile of Cluster 4, residents present strong and comprehensive demands across all dimensions. In addition to the three strategies mentioned above, such communities need to address stable funding chains and sustainable business environments. Consequently, the strategic focus should shift toward establishing structured public-private partnerships that draw on combined strengths to directly serve resident needs directly [41]. Delivered services include intelligent safety systems with real-time alerts, digital medical services with seamless access, and governance platforms that support direct resident participation [42]. To achieve stable cooperation, the governments are suggested to develop standardized contractual frameworks that clarify responsibilities, risk sharing and service delivery standards, which ensure that residents receive consistent and high-quality integrated services in safety, healthcare, and governance [43]. This clarity is critical for attracting investment and technical expertise that can be translated into tangible benefits for residents, and practical service outcomes can guarantee residents' willingness to use community services.

5 Conclusion

This study proposed and applied a multi-dimensional classification model to map the demand landscape of residents in smart community development. Drawing on a hybrid clustering approach applied to 191 survey respondents from China, four resident demand clusters were identified: Cluster 1 (weak, service-focused demand), Cluster 2 (prioritized safety and governance demand), Cluster 3 (strong community services demand), and Cluster 4 (comprehensive demand).

This study presented valuable insights in theoretical, and practically terms. On the theoretical side, it offers a data-driven taxonomy that quantitatively organizes resident demands across multiple dimensions, moving the field away from isolated and function-specific analyses toward a more integrated interpretive framework. On the practical side, the findings give policymakers and planners a concrete classification tool. Matching a community to its demand profile allows for the design of targeted interventions, ranging from building foundational digital capabilities in Cluster 1 communities to instituting collaborative governance structures in Cluster 4, thereby improving resource allocation and strengthening the strategic impact of smart city programs.

Despite these contributions, two limitations should be acknowledged. On the one hand, the model's application has been within the specific socio-political context of Chinese cities, which may affect the generalizability of the demand cluster definitions. Future research could validate and refine this taxonomy in diverse international settings. On the other hand, it is necessary to conduct a further analysis of the evolutionary pathway among the clusters of residents' demands, thereby generating more precise strategy framework for smart community development.

References

[1] N. Zhang, X. J. Zhao, and X. P. He, Understanding the relationships between information architectures and business models: An empirical study on the success configurations of smart communities, *Government Information Quarterly,* 37(2):101439, 2020.

[2] K. Jakobsen, M. Mikalsen, and G. Lilleng, A literature review of smart technology domains with implications for research on smart rural communities, *Technology in Society,* 75:102397, 2023.

[3] A. Asadzadeh, S. Pakkhoo, M. M. Saeidabad, H. Khezri, and R. Ferdousi, Information technology in emergency management of COVID-19 outbreak, *Informatics in Medicine Unlocked,* 21:100475, 2020.

[4] T. T. Gu, Q. Z. Xu, X. Y. Song, E. Y. Hao, P. Cui, and M. H. Xie, Analysis of influencing factors and their inner mechanism of the market participation in the smart community construction of China, *Ain Shams Engineering Journal,* 15(7):102761, 2024.

[5] Y. Lee, S. Han, and Y. Cho, Navigating the Path to Smart and Sustainable Cities: Insights from South Korea's National Strategic Smart City Program, *Land,* 14(5):928, 2025.

[6] N. Streitz, Beyond "smart-only' cities: redefining the "smart-everything' paradigm, *Journal of Ambient Intelligence and Humanized Computing,* 10(2):791-812, 2019.

[7] C. Gao and X. Zhao, Concept of a demand-response model for smart community construction: a case study in Ningbo, China, *Scientific Reports,* 15(1):6893, 2025.

[8] J. Guo and W. H. Ling, Impact of Smart City Planning and Construction on Community Governance under Dynamic Game, *Complexity,* 2021:6690648, 2021.

[9] S. L. Miao and H. Tan, Models and Logic of Smart Community Governance in a Centralised System, *China-an International Journal,* 23(3):45-63, 2025.

[10] T. T. Gu, D. Z. Li, and L. Z. Li, The Elderly's Demand for Community-Based Care Services and Its Determinants: A Comparison of the Elderly in the Affordable Housing Community and Commercial Housing Community of China, *Journal of Healthcare Engineering,* 2020:1840543,

2020.
[11] C. D. Vizia, E. Patti, E. Macii, and L. Bottaccioli, A User-Centric View of a Demand Side Management Program: From Surveys to Simulation and Analysis, *IEEE Systems Journal,* 16(2):1885-1896, 2022.
[12] X. Hu, Y. Li, Y. Sun, C. Zhang, W. Ding, and J. Deng, Water permits trading framework for urban water demand management based on smart metering, *Journal of Environmental Management,* 304:114208, 2022.
[13] W. Zhang, B. Guo, W. Zhao, Y. He, and X. Wang, Making Smart Cities Human-Centric: A Framework for Dynamic Resident Demand Identification and Forecasting, *Sustainability,* 17(21):9423, 2025.
[14] Y. F. Jiang, H. L. Long, Y. T. Tang, and W. Deng, Measuring the role of land consolidation to community revitalization in rapidly urbanizing rural China: A perspective of functional supply-demand, *Habitat International,* 155:103237, 2025.
[15] T. T. Gu, E. Y. Hao, C. Y. Wang, S. Y. Zhu, and Y. C. Wang, CRITIC-PROMETHEE II-Based Evaluation of Smart Community Services: A Case Study of Shenzhen, China, *Journal of the Knowledge Economy,* 16:3286–3320, 2024.
[16] P. Jinqing, L. Zhengyi, T. Yutong, J. Haihao, Y. Rongxin, and Y. Jinyue, Balancing stakeholder benefits: A many-objective optimal dispatch framework for home energy systems inspired by Maslow's Hierarchy of needs, *Advances in Applied Energy,* 13:100160, 2024.
[17] D. Zhang, Z. Li, J. Zhong, and J. Yang, A framework for prioritizing urban ecological infrastructure (UEI) implementation tasks based on residents' ecological demands and government policies, *Journal of Environmental Management,* 354:120369, 2024.
[18] X. Wang, X. X. Zhang, and J. J. He, Challenges to the system of reserve medical supplies for public health emergencies: reflections on the outbreak of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) epidemic in China, *Bioscience Trends,* 14(1):3-8, 2020.
[19] C. L. Chen, Z. Y. Lim, and H. C. Liao, Blockchain-Based Community Safety Security System with IoT Secure Devices, *Sustainability,* 13(24):13994, 2021.
[20] Y. Sha, M. Li, H. Xu, S. Zhang, and T. Feng, Smart City Public Safety Intelligent Early Warning and Detection, *Scientific Programming,* 2022(1):7552601, 2022.
[21] C. Wang, L. Wang, T. Gu, J. Yin, and E. Hao, CRITIC-TOPSIS-Based Evaluation of Smart Community Safety: A Case Study of Shenzhen, China, *Buildings,* 13(2):476, 2023.
[22] P. Sun, G. Draughon, R. Hou, and J. P. Lynch, Automated Human Use Mapping of Social Infrastructure by Deep Learning Methods Applied to Smart City Camera Systems, *Journal of Computing in Civil Engineering,* 36(4):04022011, 2022.
[23] S. Barns, E. Cosgrave, M. Acuto, and D. McNeill, Digital Infrastructures and Urban Governance, *Urban Policy and Research,* 35(1):20-31, 2017.
[24] J. Tan, J. Leng, X. D. Zeng, D. Feng, and P. L. Yu, Digital Twin for Xiegong's Architectural Archaeological Research: A Case Study of Xuanluo Hall, Sichuan, China, *Buildings,* 12(7):1053, 2022.
[25] F. K. Wang, J. Z. Zhang, and P. K. Zhang, Influencing Factors of Smart Community Service Quality: Evidence from China, *Tehnicki Vjesnik-Technical Gazette,* 28(4):1187-1196, 2021.
[26] M. Li, J. Shen, X. X. Wang, Q. Chen, X. Y. Liao, and L. Ren, A theoretical framework based on the needs of smart aged care for Chinese community-dwelling older adults: A grounded theory study, *International Journal of Nursing Knowledge,* 35(1):13-20, 2024.
[27] S. Sun, X. Y. Lyu, and J. Chen, Technology readiness and smart healthcare device usage intentions among Chinese elderly: A moderated mediation model of technology interactivity and subjective norms, *Health Informatics Journal,* 31(2):14604582251344828, 2025.
[28] D. Gagliardi, L. Schina, M. L. Sarcinella, G. Mangialardi, F. Niglia, and A. Corallo, Information and communication technologies and public participation: interactive maps and value added for citizens, *Government Information Quarterly,* 34(1):153-166, 2017.
[29] L. J. Wan and S. Q. Jiang, Research on the Influencing Factors of Sustainable Development of Smart Community, *Mathematical Problems in Engineering,* 2022:8420851, 2022.
[30] J. Y. Yin, J. Q. Wang, C. Y. Wang, L. X. Wang, and Z. Y. Chang, CRITIC-TOPSIS Based Evaluation of Smart Community Governance: A Case Study in China, *Sustainability,* 15(3):1923, 2023.
[31] L. Ivan, J. Dikken, and J. van Hoof, Unveiling the experienced age-friendliness of older people in Bucharest: A comprehensive study using the validated Romanian age-friendly cities and communities questionnaire and cluster analysis, *Habitat International,* 143:102973, 2024.
[32] R. Inbakaran and M. Jackson, Resident Attitudes Inside Victoria's Tourism Product Regions: A Cluster Analysis, *Journal of Hospitality and Tourism Management,* 13(1):59-74, 2006.
[33] F. Yang, X. G. Wen, A. Aziz, and A. K. Luhach, The need for local adaptation of smart infrastructure for sustainable economic management,

Environmental Impact Assessment Review, 88:106565, 2021.
[34] H. Guo, C. C. Yang, B. B. Liu, and F. Yang, Performance-based contracts in the sharing economy: A supply chain framework with application of Internet of Things, *Annals of Operations Research,* 326(SUPPL 1):1, 2023.
[35] B. Choudhuri, P. R. Srivastava, S. K. Mangla, and Y. Kazancoglu, Enterprise architecture as a responsible data driven urban digitization framework: enabling circular cities in India, *Annals of Operations Research,* 354(1):193-221, 2025.
[36] G. Esposito, A. Terlizzi, M. Guarino, and N. Crutzen, Interpreting digital governance at the municipal level: Evidence from smart city projects in Belgium, *International Review of Administrative Sciences,* 90(2):301-317, 2024.
[37] H. M. S. Badar, K. Mahmood, W. Akram, Z. Ghaffar, M. Umar, and A. K. Das, Secure authentication protocol for home area network in smart grid-based smart cities, *Computers & Electrical Engineering,* 108:108721, 2023.
[38] Z. J. Yan, L. Jiang, X. L. Huang, L. F. Zhang, and X. X. Zhou, Intelligent urbanism with artificial intelligence in shaping tomorrow's smart cities: current developments, trends, and future directions, *Journal of Cloud Computing-Advances Systems and Applications,* 12(1):179, 2023.
[39] A. S. Sani, E. Bertino, D. Yuan, K. Meng, and Z. Y. Dong, SPrivAD: A secure and privacy-preserving mutually dependent authentication and data access scheme for smart communities, *Computers & Security,* 115:102610, 2022.
[40] J. Y. Cho and S. K. Park, Key factors for sustainable operation of smart rural communities in aging societies: Voices of Korean community leaders, *Technology in Society,* 74:102306, 2023.
[41] G. Siokas, V. Kelaidi, and A. Tsakanikas, The smart city as a hub for nourishing public-private partnerships, *Sustainable Cities and Society,* 76:103466, 2022.
[42] D. Ali *et al.*, Integrating private health facilities in government-led health systems: a case study of the public-private mix approach in Ethiopia, *Bmc Health Services Research,* 22(1):1477, 2022.
[43] C. Benitez-Avila, A. Hartmann, and G. Dewulf, Contractual and Relational Governance as Positioned-Practices in Ongoing Public-Private Partnership Projects, *Project Management Journal,* 50(6):716-733, 2019.