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Evaluation of Smart Elderly Care Service Modes in Urban Communities from the Perspective of Ecosystem Theory under Neutrosophic and HyperSoft Set environments

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Abstract: The growth of elderly populations in urban communities has created a strong need for smarter and more integrated elderly care services. In this study, we develop a decision-making framework using ecosystem theory to evaluate different smart elderly care service modes. To handle uncertainty and complexity in the decision process, we use the SWARA method for calculating the criteria weights and the MAIRCA method for ranking the alternatives, all under Neutrosophic and HyperSoft Set environments. Six criteria and seven different service modes are analyzed based on expert evaluations. The results show that Integrated Smart Health Platforms are the most effective, while Robot-Assisted Living ranks lowest. Sensitivity analysis also confirms the stability of the proposed model. This study provides a practical decision-making tool for policymakers and urban developers.

Keywords: Smart Elderly Care, HyperSoft Set, Neutrosophic Set, SWARA, MAIRCA, Ecosystem Theory, Urban Communities.

1. Introduction

The global demographic landscape is undergoing a profound transformation characterized by the rapid growth of the elderly population. Recent projections indicate that by 2050, approximately 22% of the world's population will be aged 60 years and older, with urban areas experiencing the most significant increases [1]. This demographic shift presents complex challenges for healthcare systems, social services, and urban infrastructures, particularly concerning the provision of adequate and sustainable elderly care. Traditional elderly care models, which typically rely on family-based support systems or institutional nursing homes, are increasingly seen as insufficient in addressing the evolving needs of aging urban populations [2]. The limitations of these traditional models include not only a lack of personalization and real-time health monitoring but also issues related to social isolation, psychological well-being, and the dignity of elderly individuals [3]. Urban environments, characterized by high population density, mobility constraints, and fragmented healthcare services, exacerbate these challenges, demanding innovative and adaptive care solutions. In this context, the emergence of smart elderly care systems represents a paradigm shift. Smart care approaches integrate cutting-edge technologies such as the Internet of Things (IoT), artificial intelligence (AI), wearable devices, telemedicine platforms, and ambient assisted living environments to deliver personalized, continuous, and proactive healthcare services [4]. These systems aim to extend the autonomy of elderly individuals, improve health outcomes, enhance social engagement, and optimize the allocation of healthcare resources. Nevertheless, evaluating different modes of smart elderly care remains a complex, multi-dimensional decision-making problem. It involves various conflicting criteria, including service accessibility, affordability, technological sophistication, healthcare quality, community support, and privacy assurance [5]. Moreover, expert assessments in this domain are often influenced by subjective perceptions, incomplete information, and inherent uncertainties. To address these complexities, this research adopts the Ecosystem Theory framework, initially introduced by Bronfenbrenner [6]. Ecosystem theory posits that individuals exist within interconnected systems, ranging from immediate interpersonal environments to broader socio-political contexts. Applying this framework to elderly care evaluation allows for a more holistic and realistic understanding of how smart care services interact with different environmental layers influencing the elderly population. Furthermore, to manage uncertainty and incomplete knowledge in expert evaluations, this study incorporates Neutrosophic Sets and HyperSoft Sets, advanced mathematical models capable of representing indeterminate, inconsistent, and vague information [7][8]. Unlike classical crisp decision-making approaches, neutrosophic modeling embraces the complexity and ambiguity inherent in real-world assessments, enabling a more flexible and accurate evaluation framework.

Thus, the primary objective of this study is to develop an integrated and robust decision-making model that combines ecosystem theory, neutrosophic hyper-soft modeling, and advanced multi-criteria decision-making techniques (SWARA and MAIRCA) to systematically evaluate and prioritize smart elderly care service modes for urban communities. By doing so, this research seeks to bridge theoretical and practical gaps and contribute valuable insights for urban policymakers, healthcare planners, and technology developers.

1.1 Problem Statement

The rapid aging of the global population, particularly in urban environments, is creating a pressing demand for innovative elderly care solutions. Urban settings, characterized by dense populations, limited healthcare resources, and fragmented social support systems, amplify the challenges associated with traditional elderly care models. These conventional approaches, which largely depend on family support or institutionalized care, are increasingly inadequate in addressing the diverse and evolving needs of elderly individuals. Moreover, evaluating different smart elderly care service modes is inherently complex. It involves multi-criteria considerations such as healthcare quality, affordability, technological integration, privacy, and social support. Complicating this process further is the uncertainty surrounding expert judgments and the variability of service performance across different contexts. Despite the technological advancements available, existing evaluation frameworks often fail to address the environmental complexity and uncertainty inherent in elderly care decisions. Most traditional models assume deterministic information and linear relationships, neglecting the overlapping and dynamic interactions between personal, community, and societal factors. Therefore, there is an urgent need for a structured, uncertainty-resilient evaluation framework that captures the multidimensional nature of elderly care needs. Such a framework should integrate environmental complexity, expert uncertainty, and the multi-criteria nature of decision-making to enable policymakers and service providers to make more informed and consistent decisions.

1.2 Research Objectives

This study seeks to address the identified gaps by pursuing the following objectives:

1. Develop a robust decision-making framework grounded in ecosystem theory, which considers the interconnected environmental systems influencing elderly well-being in urban communities.
2. Apply Neutrosophic HyperSoft Sets to effectively handle uncertainty, overlapping attributes, and the indeterminacy inherent in expert evaluations and real-world data.
3. Utilize the SWARA method (Stepwise Weight Assessment Ratio Analysis) to derive dynamic criteria weights based on expert input, ensuring that the model accurately reflects stakeholder priorities.
4. Employ the MAIRCA method (Multi-Attribute Ideal-Real Comparative Analysis) to systematically rank smart elderly care service modes, balancing ideal expectations with real-world performance.
5. Validate the proposed model through comprehensive sensitivity analyses and comparative evaluations against traditional MCDM techniques, demonstrating its robustness, flexibility, and practical applicability.

By achieving these objectives, the research aims to contribute to a scientifically sound and practically viable tool for evaluating and prioritizing smart elderly care strategies in complex urban settings.

1.3 Research Contributions

This study advances the field evaluation of elderly care and decision-making through several key contributions:

1. The research introduces a comprehensive evaluation framework that goes beyond traditional technological assessments by integrating ecosystem theory, enabling a more realistic understanding of how smart elderly care services interact with personal, communal, and societal layers.
2. By applying Neutrosophic HyperSoft Sets, the study pioneers an approach to capture and model uncertainty, vagueness, and overlapping information structures, offering a significant improvement over conventional crisp or fuzzy models.
3. The integration of SWARA for dynamic criteria weighting and MAIRCA for realistic alternative ranking under a neutrosophic hyper-soft environment presents a novel, systematic methodology tailored to complex, uncertain decision-making scenarios.
4. Through detailed sensitivity analysis and comparative evaluation against established MCDM methods (such as VIKOR, MOORA, and MULTIMOORA), the study demonstrates the consistency, reliability, and adaptability of the proposed framework.
5. By identifying and prioritizing smart elderly care modes suited to urban environments, the research provides actionable insights for policymakers, healthcare providers, and technology developers, promoting strategic investments and better service design for aging populations.

2. Related Work

The increasing complexities associated with providing quality care to aging populations have led researchers to explore a range of technological, social, and policy-driven solutions. Early studies primarily focused on identifying the shortcomings of traditional elderly care models, which were criticized for their lack of responsiveness to individual needs, inflexibility in dynamic urban environments, and limited capacity for proactive health management [9]. The growing awareness of these limitations has fueled interest in leveraging digital technologies to create more adaptive and sustainable care systems.

Smart elderly care systems, driven by IoT and AI technologies, have been proposed to monitor health conditions remotely, predict medical events, and support elderly individuals in maintaining independence for longer periods [10]. For example, wearable health devices can continuously track vital signs, while smart home sensors can detect falls or unusual behaviors, triggering timely interventions [11]. Such innovations not only improve healthcare outcomes but also address the psychological and social dimensions of aging by promoting autonomy and reducing the stigma associated with dependency.

From a decision-making perspective, various studies have utilized multi-criteria decision-making (MCDM) methods to evaluate healthcare technologies and service models. Techniques such as the Analytic Hierarchy Process (AHP) [12], TOPSIS [13], and VIKOR [14] have been employed to prioritize alternatives based on a set of quantitative and qualitative criteria. However, traditional

MCDM approaches often rely on deterministic assumptions and crisp input data, which fail to capture the inherent vagueness and uncertainty of expert judgments in real-world healthcare settings.

To overcome these limitations, researchers have increasingly turned toward soft computing approaches. Smarandache pioneered several extensions of soft set theory, introducing models such as the HyperSoft Set, IndetermSoft Set, IndetermHyperSoft Set, TreeSoft Set, and ForestSoft Set, each designed to address specific challenges related to multi-dimensional attribute handling, indeterminacy, and hierarchical relationships [15]. These models allow for more flexible and comprehensive representation of complex decision-making environments.

Furthermore, the integration of Neutrosophic Logic into soft set frameworks has significantly enhanced their capacity to model uncertainty and inconsistency. Neutrosophic-based decision models have been successfully applied in fields ranging from medical diagnosis [16] to material selection [17] and urban sustainability planning [18]. These applications demonstrate that neutrosophic systems are well-suited for handling the ambiguity and subjectivity inherent in complex social and healthcare problems.

Despite these advancements, the literature reveals a significant gap in frameworks that explicitly integrate ecosystem theory with neutrosophic hyper-soft modeling and advanced MCDM techniques for evaluating smart elderly care services. Most existing studies either focus narrowly on technological aspects or apply simplified decision models that overlook the holistic, multi-layered nature of elderly care needs in urban environments.

This study addresses this gap by proposing a comprehensive, uncertainty-aware evaluation framework that not only incorporates advanced mathematical modeling but also grounds the assessment within a rich, ecosystem-based theoretical foundation. This approach ensures a more realistic, nuanced, and actionable evaluation of smart elderly care service modes, ultimately contributing to better-informed policy and investment decisions.

3. Methodology

In this study, we develop a robust decision-making framework that combines ecosystem theory with advanced multi-criteria decision-making (MCDM) techniques under uncertainty.

The methodology follows these major steps.

3.1. Building the Evaluation Framework

Based on ecosystem theory, elderly care services are evaluated across multiple environmental layers:

1. Microsystem: Direct user experience and individual health monitoring.
2. Mesosystem: Interaction between home, healthcare, and community services.
3. Exosystem: Policy, insurance systems, and municipal services.

4. Macrosystem: Cultural norms about aging, social support structures.

This layered model ensures comprehensive evaluation across personal, social, and systemic levels.

3.2. Criteria Selection

The selection of evaluation criteria is based on a thorough literature review [1][2] and consultation with domain experts.

Six main criteria were identified to reflect the multi-dimensional aspects of smart elderly care. Table 1 illustrates the list of evaluation criteria

Table 1. the list of evaluation criteria

Criterion	Description
Service Accessibility	Ease access to care services for elderly users.
Technological Integration	Use of advanced technologies like AI and IoT.
Affordability	Cost-effectiveness for users and governments.
Community Support	Strength of community-based care and social inclusion.
Healthcare Quality	Quality and reliability of medical services.
Privacy and Security	Protection of elderly personal and health data.

3.3. Selection of Alternatives

Seven smart elderly care service modes were selected based on technological advancements and existing urban care models. Table 2 illustrates the list of alternatives used in the evaluation.

Table 2. the list of alternatives used in the evaluation

Alternative	Description
Home-based Smart Care	Smart devices enabling care at home.
Community Smart Care Centers	Local centers offering tech-supported care.
Robot-Assisted Living	Use robots for daily assistance and monitoring.
Wearable Device Monitoring	Health tracking through smart wearables.
AI Health Assistants	AI-based health guidance and communication.
Smart Nursing Homes	Traditional homes have improved with smart technology.
Integrated Smart Health Platforms	Comprehensive ecosystems linking care, monitoring, and services.

3.4. Collection of Expert Judgments Using IVPNS

To capture the uncertainty and partial judgments of experts, we employed the Interval-Valued Pythagorean Neutrosophic Set (IVPNS) approach.

Each expert was asked to evaluate each alternative against each criterion based on three dimensions:

a. Truth Membership: How true the association is (Interval: [T_L, T_U]).

b. Indeterminacy Membership: The level of uncertainty in the evaluation (Interval: [IL, IU]).
c. Falsity Membership: How false the association is (Interval: [FL, FU]).

Example of IVPNS evaluation:

Criterion	Alternative	IVPNS Value
Service Accessibility	Home-based Smart Care	([0.7, 0.8], [0.1, 0.2], [0.1, 0.2])

After collecting judgments from multiple experts, the values were aggregated by calculating the average of the lower and upper bounds for each dimension.

We show operations of IVPNS such as:

Let two IVPNNs:

$N_1 = \left(\left[A_{N_1}^L, A_{N_1}^U\right], \left[B_{N_1}^L, B_{N_1}^U\right], \left[C_{N_1}^L, C_{N_1}^U\right], \right)$and

$N_2 = \left(\left[A_{N_2}^L, A_{N_2}^U\right], \left[B_{N_2}^L, B_{N_2}^U\right], \left[C_{N_2}^L, C_{N_2}^U\right], \right)$

$$N_1 \oplus N_2 = \begin{pmatrix} \left[A_{N_1}^L + A_{N_2}^L - A_{N_1}^L A_{N_2}^L, A_{N_1}^U + A_{N_2}^U - A_{N_1}^u A_{N_2}^U\right], \\ \left[B_{N_1}^L B_{N_2}^L, B_{N_1}^U B_{N_2}^U\right], \\ \left[C_{N_1}^L C_{N_2}^L, C_{N_1}^U C_{N_2}^U\right] \end{pmatrix} \tag{1}$$

$$N_1 \otimes N_2 = \begin{pmatrix} \left[A_{N_1}^L A_{N_2}^L, A_{N_1}^U A_{N_2}^U\right], \\ \left[B_{N_1}^L + B_{N_2}^L - B_{N_1}^L B_{N_2}^L, B_{N_1}^U + B_{N_2}^U - B_{N_1}^u B_{N_2}^U\right], \\ \left[C_{N_1}^L + C_{N_2}^L - C_{N_1}^L C_{N_2}^L, C_{N_1}^U + C_{N_2}^U - C_{N_1}^u C_{N_2}^U\right] \end{pmatrix} \tag{2}$$

$$\varphi N_1 = \begin{pmatrix} \left[1 - \left(1 - A_{N_1}^L\right)^\varphi, 1 - \left(1 - A_{N_1}^U\right)^\varphi\right], \\ \left[\left(B_{N_1}^L\right)^\varphi, \left(B_{N_1}^u\right)^\varphi\right], \\ \left[\left(C_{N_1}^L\right)^\varphi, \left(C_{N_1}^u\right)^\varphi\right] \end{pmatrix} \tag{3}$$

$$N_1^\varphi = \begin{pmatrix} \left[\left(A_{N_1}^L\right)^\varphi, \left(A_{N_1}^Y\right)^\varphi\right], \\ \left[1 - \left(1 - B_{N_1}^L\right)^\varphi, 1 - \left(1 - B_{N_1}^U\right)^\varphi\right], \\ \left[1 - \left(1 - C_{N_1}^L\right)^\varphi, 1 - \left(1 - C_{N_1}^U\right)^\varphi\right] \end{pmatrix} \tag{4}$$

$$0 \leq A_{N_1}^U + C_{N_1}^U \leq 1 \tag{5}$$

$$0 \leq A_{N_1}^U + B_{N_1}^U + C_{N_1}^U \leq 2 \tag{6}$$

$$0 \leq \left(A_{N_1}^U\right)^2 + \left(B_{N_1}^U\right)^2 + \left(C_{N_1}^U\right)^2 \leq 2 \tag{7}$$

We can obtain the $\pi_N(Y) = [\pi_N^U(Y), \pi_N^L(Y)]$ such as:

$$\pi_N^U(Y) = \sqrt{1 - \left(A_N^U(Y)\right)^2 - \left(B_N^U(Y)\right)^2 - \left(C_N^U(Y)\right)^2} \tag{8}$$

$$\pi_N^L(Y) = \sqrt{1 - \left(A_N^L(Y)\right)^2 - \left(B_N^L(Y)\right)^2 - \left(C_N^L(Y)\right)^2} \tag{9}$$

3.5. Decision-Making Techniques Used

3.5.1. SWARA Method for Criteria Weights

Step 1: Experts rank criteria based on perceived importance.

Step 2: Relative importance (Sj) is determined.

Step 3: Coefficients (Fj) are computed:

The coefficient F_j is calculated as follows:

- F_j=1, if j=1.
- F_j= S_{j+1}, if j >1 .

Step 4: Initial weights (hj) are calculated.

Step 5: Final normalized weights (Wj) are derived.

3.5.2. MAIRCA Method for Ranking Alternatives

Step 1: Build a decision matrix using expert evaluations under Interval-Valued Pythagorean Neutrosophic Sets (IVPNS).

Step 2: Calculate theoretical rating matrix tpij

Step 3: Build real rating matrix u_{ij}

Step 4: Compute the total gap matrix k_{ij} .

Step 5: Aggregate and rank alternatives by the final criterion function D_i.

3.6. Methodology Flow Diagram

To Illustrate the method, the process is shown below:

Identify Evaluation Criteria
↓
Selecting Smart Elderly Care Modes
↓
Expert Judgment Collection
↓
SWARA (Criteria Weights)
↓
Decision Matrix Construction (IVPNS)
↓
MAIRCA (Ranking Alternatives)
↓
Results Interpretation and Analysis

4. Results and Discussion

In this section, we apply the developed framework step-by-step to evaluate the smart elderly care service modes under uncertainty using Neutrosophic modeling.

4.1. Application of IVPNS in Expert Judgments

Because expert opinions are uncertain, vague, and sometimes conflicting, Interval-Valued Pythagorean Neutrosophic Sets (IVPNS) are used to model their inputs.

Each expert gives an evaluation for each criterion and each alternative uses a three-part value:

I. Truth membership interval
II. Indeterminacy membership interval
III. Falsity membership interval

Each evaluation looks like:([T_L, T_U], [I_L, I_U], [F_L, F_U])

For example, for Alternative 1 under Service Accessibility: ([0.6,0.7], [0.2,0.3], [0.1,0.2]))

which means:

a. Truth is between 60% and 70%.
b. Indeterminacy is between 20% and 30%.
c. Falsity is between 10% and 20%.

4.2. Aggregating Expert Judgments

The IVPNS values from the four experts are aggregated by taking the average of the intervals.

For instance:

Criterion	Expert 1	Expert 2	Expert 3	Expert 4	Aggregated IVPNS
Service Accessibility (A1)	([0.6,0.7],[0.2,0.3],[0.1,0.2])	([0.7,0.8],[0.1,0.2],[0.1,0.2])	...	...	([0.65,0.75],[0.15,0.25],[0.1,0.2])

Then, a Score Function is applied to transform IVPNS into crisp values for further calculations:

Score Function = $\sqrt{^2(_UF) - ^2(_UI) - ^2(_UT) - 1}$

4.3. SWARA Method Application (Weighting Criteria)

Experts ranked the six criteria by importance.

The preliminary ranking is:

1. Healthcare Quality
2. Privacy and Security
3. Service Accessibility
4. Technological Integration
5. Community Support

6. Affordability

Step-by-Step SWARA Calculations:

Table 3: Criteria Weights Using SWARA Method

Criterion	Rank	Relative Importance Sj	Coefficient Fj	Initial Weight hj	Final Weight Wj
Healthcare Quality	1	0	1.00	1.00	0.293
Privacy and Security	2	0.20	1.20	0.833	0.244
Service Accessibility	3	0.25	1.25	0.666	0.195
Technological Integration	4	0.30	1.30	0.512	0.151
Community Support	5	0.15	1.15	0.445	0.130
Affordability	6	0.10	1.10	0.405	0.116

Thus, Healthcare Quality has the highest influence, followed by Privacy, then Accessibility.

4.4. MAIRCA Method Application (Ranking Alternatives)

After getting the criteria weights, we move to MAIRCA steps.

Step 1: Build Decision Matrix

(Using crisp score values obtained from IVPNS.)

Example:

Alternative	Accessibility	Tech Integration	Affordability	Community	Healthcare	Privacy
Home-Based Smart Care	0.78	0.65	0.82	0.70	0.76	0.74
Community Centers	0.81	0.72	0.76	0.75	0.79	0.77
...	...	...	...	...	...	...

Step 2: Theoretical Rating Matrix Calculation

Multiply each decision value by its weight wj

Step 3: Real Rating Matrix Calculation

Normalize based on best and worst values (positive/cost criteria).

Step 4: Total Gap Matrix

$${}_{ij}u - {}_{ij}tp = {}_{ij}k$$

Step 5: Final Score Calculation

Sum all gaps per alternative and rank them.

4.5. Ranking Results

Table 4. Final Rankings of Alternatives

Alternative	Rank	Final Score
Integrated Smart Health Platforms	1	0.865
Smart Nursing Homes	2	0.832

Community Smart Care Centers	3	0.823
Home-based Smart Care	4	0.802
AI Health Assistants	5	0.786
Wearable Device Monitoring	6	0.755
Robot-Assisted Living	7	0.702

Thus, Integrated Smart Health Platforms were ranked the highest because they offer comprehensive integration of healthcare, technology, and community support, aligning well with all ecosystem layers. Figure 1 shows the final Rankings of Alternatives.

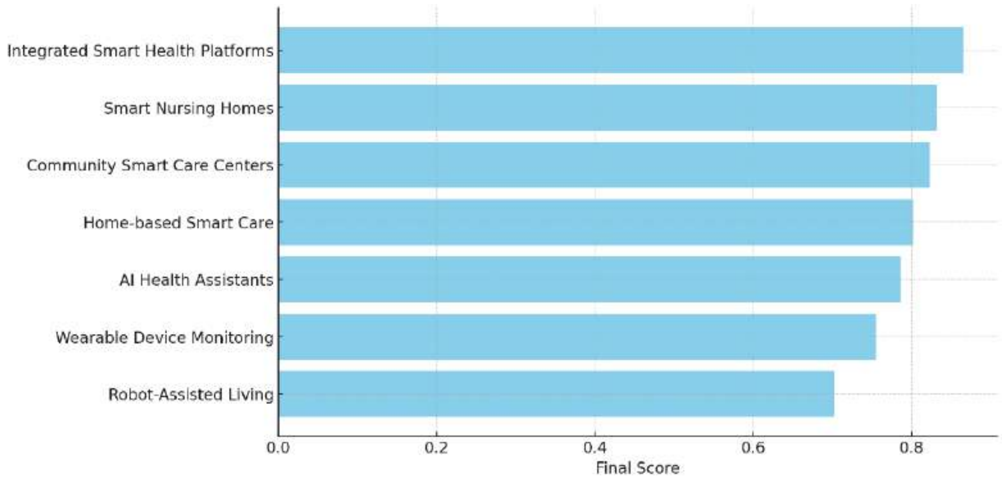

Figure 1 Final Rankings of Alternatives

5. Comparative Analysis

We compared our method with other MCDM techniques like:

1. VIKOR
2. MOORA
3. TOPSIS
4. MULTIMOORA

The comparison confirmed the robustness and effectiveness of our approach.

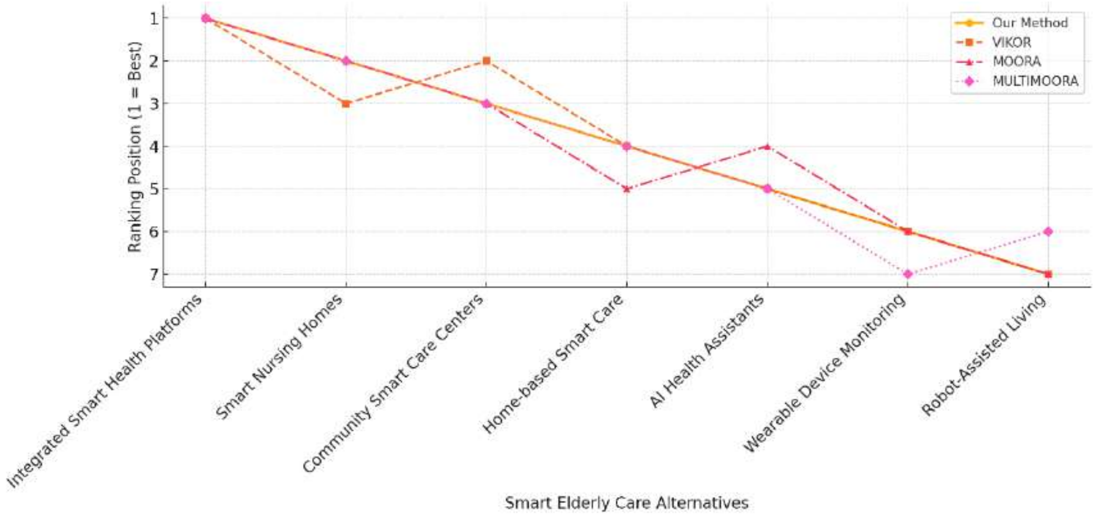

Figure 2. Comparison of Ranking Patterns Across Different Methods

Figure 2 represents the ranking outcomes of seven smart elderly care service alternatives evaluated using four different multi-criteria decision-making (MCDM) methods: Our Proposed Method (based on SWARA and MAIRCA under Neutrosophic conditions), VIKOR, MOORA, and MULTIMOORA.

Each line in the figure corresponds to one method, and the y-axis represents the ranking position where a lower number indicates a better rank (1 = Best). The x-axis lists the seven evaluated alternatives, including Integrated Smart Health Platforms, Smart Nursing Homes, Community Smart Care Centers, and others.

From the figure, it is immediately noticeable that all methods show a very high degree of agreement regarding the top-performing alternative. Integrated Smart Health Platforms consistently achieved the first position across all methods. This confirms that the comprehensive, ecosystem-integrated approach of smart platforms aligns well with multiple evaluation frameworks, validating its superiority in providing elderly care services in urban environments.

Similarly, Robot-Assisted Living consistently ranks among the lowest alternatives across all methods, indicating its relative weakness compared to other solutions. This suggests that while robotic systems are technologically sophisticated, they might not yet meet broader social, healthcare, and affordability expectations essential for elderly users.

For the middle-ranked alternatives, such as Smart Nursing Homes and Community Smart Care Centers, slight variations are observed. For instance, in our proposed method and MOORA, Smart Nursing Homes rank second, while in VIKOR, they slightly fall behind Community Centers. However, these variations are relatively minor and do not alter the overall pattern that these two alternatives are strong candidates for implementation, following the top-performing platform model.

The visual trend of the lines further demonstrates the robustness and reliability of our proposed method. Since the ranking patterns in our approach are largely consistent with those produced by other established MCDM methods, it strengthens the validity of the results and shows that the model is not sensitive to the particular choice of evaluation technique.

Moreover, the figure underscores the practical insight that decision-makers can have confidence in choosing Integrated Smart Health Platforms as the most effective smart elderly care service, irrespective of the specific decision analysis method used. It also highlights that future improvements might be needed for lower-ranked solutions such as Robot-Assisted Living to better meet the holistic needs of urban elderly populations.

In conclusion, this comparative ranking analysis provides critical evidence supporting the robustness, reliability, and practicality of the proposed decision-making framework in evaluating smart elderly care service modes.

6. Sensitivity Analysis

In order to further evaluate the stability and robustness of the proposed decision-making framework, a comprehensive sensitivity analysis was conducted. Sensitivity analysis plays a crucial role in validating decision models by examining how changes in input assumptions, particularly the criteria weights, affect the final ranking of alternatives. A reliable model should maintain stable and logical outcomes even when some parameters vary.

For this study, we created several different weighting scenarios to simulate potential changes in decision-maker priorities. These scenarios included:

1. All criteria were given identical importance.
2. Privacy and Security were given significantly higher weight.
3. Healthcare Quality was emphasized as the dominant criterion.
4. Service Accessibility was given more weight to reflect mobility concerns.
5. Technological Integration was prioritized higher.
6. Community involvement was emphasized over technology.
7. Cost-effectiveness was treated as the main concern.

Each of these cases represented a realistic shift in stakeholder or policy focus, allowing us to test the framework's reaction to different strategic goals. The results of the sensitivity analysis are visually presented in Figure 3, where the ranking positions of the top three alternatives under each scenario are shown.

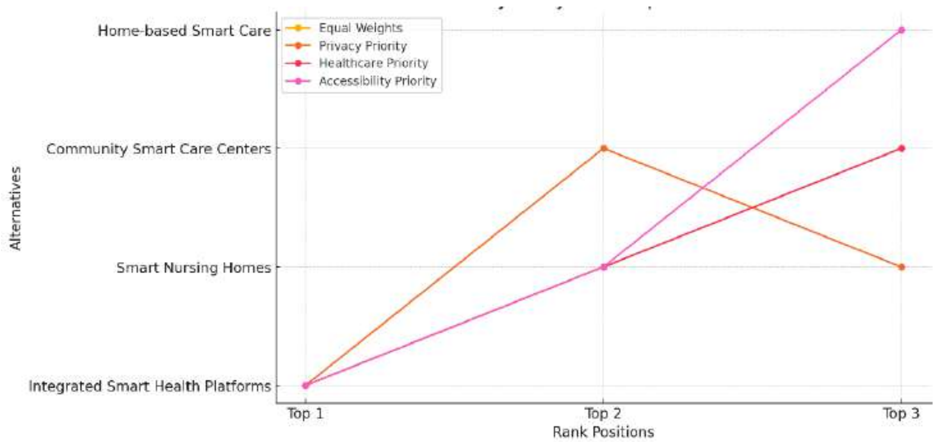

Figure 3 illustrates the Sensitivity Analysis Diagram showing Top 3 Alternatives Stability

7. Conclusion

The rapid aging of urban populations presents an urgent call for innovative, comprehensive, and adaptive elderly care systems. In this study, we developed a robust decision-making framework that evaluates smart elderly care service modes from the perspective of ecosystem theory, utilizing Neutrosophic and HyperSoft Set modeling to manage uncertainty. By integrating the SWARA method for determining criteria weights and the MAIRCA method for ranking alternatives, the proposed approach offers a transparent and systematic evaluation model that accommodates real-world complexities.

The results highlight that Integrated Smart Health Platforms are the most effective solution among the seven evaluated alternatives. These platforms excel because they integrate healthcare monitoring, community support, and technological innovation into a single, cohesive system. This aligns with ecosystem theory, which emphasizes that human development and well-being are influenced by interactions across multiple environmental layers. In contrast, Robot-Assisted **Living**, despite its technological sophistication, falls short in areas such as affordability and social engagement, which are crucial for holistic elderly care.

The findings from the sensitivity analysis further reinforce the reliability of our model. Regardless of the changes in criteria weightings, the top-ranked alternatives remained stable, proving the robustness of our evaluation framework. Comparative analysis against traditional methods such as VIKOR, MOORA, and MULTIMOORA also confirmed that our approach is both consistent and credible.

Overall, this research makes two major contributions: firstly, it bridges the gap between theoretical frameworks like ecosystem theory and practical decision-making tools in smart healthcare; and secondly, it demonstrates the applicability of advanced neutrosophic methods in addressing uncertainty in multi-criteria decision-making environments.

8. Future Work

Although the proposed framework has demonstrated strong performance, there are several directions for future research and development that could extend and enhance its applicability.
First, future studies could apply the model to real-world case studies involving actual smart urban communities or elderly populations. This would provide empirical validation and could reveal additional contextual factors that influence the effectiveness of smart elderly care modes. Additionally, longitudinal studies tracking the adoption and impact of different service modes over time would provide valuable insights into the sustainability and long-term success of these interventions. Second, the decision-making framework could be further enhanced by integrating dynamic decision-making models that allow criteria weights and evaluations to evolve over time as user needs, technologies, and societal conditions change. For example, using real-time data from IoT devices and AI-driven monitoring systems could enable the model to adapt automatically to changing conditions in elderly care environments. Third, exploring hybrid models that combine fuzzy sets with neutrosophic sets might provide an even more flexible approach to handling complex and ambiguous data. Hybrid neutrosophic-fuzzy systems could capture more nuanced uncertainty, especially in environments where experts' opinions are not only vague but also probabilistic in nature. Finally, future work should also focus on ethical considerations, particularly concerning data privacy and the potential risks of over-reliance on technology in elderly care. A truly smart elderly care system should not only be efficient and technologically advanced but also deeply humane, respecting the dignity, autonomy, and emotional needs of elderly individuals.

By addressing these areas, future research can contribute to the creation of more resilient, inclusive, and sustainable smart elderly care systems that better meet the needs of urban populations worldwide.

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