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Article

Acoustic assessment in urban residential environments: A GINI-OOB approach

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Abstract: Urban sustainable development faces significant challenges, with low Resident Value Perception (RVP) acting as a major barrier to the rapid growth and sustainability of cities. This study aims to identify the key factors influencing RVP and assess their impacts, focusing on Wuhan as the case study. An RVP indicator system is developed, integrating three dimensions, and the Fuzzy Comprehensive Evaluation-Attribute Hierarchy Model (FCE-AHM) method is employed to calculate the RVP index. Additionally, a novel GINI-out-of-bag (GINI-OOB) coupling assessment method is introduced to determine the influence of each indicator, using data from Wuhan's 2022 social satisfaction survey in China. Special emphasis is placed on the relationship between these factors and the acoustic environment. The research findings highlight the following: (1) The proposed methodology effectively identifies the key factors influencing residents' value perceptions and quantifies their levels of influence; (2) Hospital waiting times, housing price acceptability, and parking management emerge as the top three factors affecting residents' value perception, with a combined GINI-OOB index score of 0.4914. Notably, parking management has a significant influence, directly exacerbating traffic noise issues. These factors collectively impact the acoustic environment, thereby influencing residents' quality of life and overall satisfaction. This study introduces an innovative theoretical framework for evaluating urban sustainability, offering valuable insights for enhancing the assessment of residents' value perceptions and supporting policy recommendations aimed at optimizing urban acoustic environments.

Keywords: urban acoustic environment; urban sustainable development; resident's value perception; FCE-AHM; GINI-OOB

1. Introduction

Resident Value Perception (RVP) is influenced by multiple factors. Firstly, the quality of the urban environment plays a pivotal role. Inadequate air and water quality, along with severe environmental pollution, can significantly diminish RVP [1]. Therefore, it is imperative to implement effective measures for environmental protection and pollution control in order to enhance RVP. Secondly, optimal urban infrastructure and public services encompassing efficient transportation [2], education, healthcare, and cultural facilities can augment resident's satisfaction levels. Additionally, social equity, economic opportunities, and social inclusivity also hold substantial significance in this regard. The presence of inequalities and social injustices within a city can adversely impact RVP.

Urban planning and management departments can utilize this research to gain a deeper understanding of resident's needs and expectations, thereby formulating policies and plans that are more aligned with the prevailing circumstances. This will enable cities to better cater to resident's requirements and enhance resident's satisfaction. Understanding the factors influencing RVP can effectively address urban challenges such as environmental protection, traffic congestion, and housing issues [3]. By meeting resident's needs, cities can successfully achieve sustainable development goals [4]. Therefore, investigating RVP constitutes a crucial step towards achieving sustainable urban development.

The research on RVP has attracted significant attention in the fields of urban planning and sustainable development. Studies in this area encompass a wide range and can be classified based on various research methodologies and perspectives.

In terms of research methods, they can be classified into quantitative research and qualitative research. In relation to quantitative research, Vorkinn and Riese [5] utilized questionnaire surveys to measure the relationship between resident's environmental concerns and their attachment to specific places, uncovering a significant correlation between individual's emotional connections and their concerns regarding environmental issues. Moudon et al. [6] suggested an empirical approach for identifying quantifiable attributes and thresholds of walkable communities. The study employed bivariate and multivariate analysis methods to define "walkable communities" and explored factors related to resident's walking behavior. In qualitative research, Devine-Wright and Howes [7] used in-depth interviews and content analysis methods to understand community resident's views on wind energy projects and their perceptions of the potential impacts of these projects on the environment and sense of place. Additionally, Williams and Vaske [8] developed a psychological measurement method to assess resident's attachment to specific locations.

In addition to variations in research methodologies, studies on RVP have yielded divergent findings from multiple perspectives. Specifically, these can be summarized through the lenses of environmental factors, societal aspects, and economic considerations. Regarding environmental factors, Buttazzoni et al. [9] focused on the influence of the urban environment on the psychological well-being of young city dwellers and emphasized its significance for RVP. Furthermore, Gifford [10] examined how environmental psychology affects RVP by highlighting the impact of environmental factors on resident's emotions and behaviors. From a social perspective, Putnam [11] explored the concept of social capital with a particular focus on community and social participation's effect on RVP. In other dimensions within this factor, Pretty et al. [12] investigated the impact of physical exercise in natural environments on both health and psychological well-being from a social perspective. Furthermore, focusing on the economic aspect, Kahneman and Deaton [13] examined the happiness levels of urban residents, emphasizing the interaction between economic conditions and RVP.

Despite some progress in existing research on the influencing factors of RVP, the current methods primarily rely on traditional factor analysis [14], multiple regression analysis [14], and structural equation modeling [15], which are considered simplistic data mining techniques. These approaches have limitations in deeply exploring and explaining the complexity of RVP's influencing factors. Therefore, it is crucial to introduce machine learning techniques for a more profound understanding and comprehensive analysis of these factors. Assessing resident's value perception poses several challenges such as data heterogeneity, nonlinear relationships, and the multi-level nature of influencing factors. Simple questionnaire surveys and basic statistical analyses struggle to accurately capture and explain the intricate interactions between these factors [14]. Hence, constructing an effective and universal system along with a methodology for mining RVP's influencing factors becomes essential. Machine learning emerges as a powerful tool for data analysis that can automatically identify patterns through algorithms while effectively predicting unknown data behavior [16]; thus uncovering hidden relationships between variables. Machine learning possesses robust capabilities in handling nonlinear relationships and exhibits adaptability to complex data structures, thereby significantly enhancing our understanding of the formation mechanisms underlying resident's perception of value.

Commonly employed techniques in the field of machine learning include Support Vector Machines (SVM), Decision Trees (DT), Artificial Neural Networks (ANN), and Light Gradient Boosting Machine (LightGBM). SVM and DT are algorithms that classify data by partitioning hyperplanes, showcasing remarkable computational efficiency [17,18]. However, when dealing with multidimensional complex indicator data, these algorithms exhibit certain limitations in handling nonlinear relationships and intricate high-dimensional data interactions, resulting in reduced robustness. ANN employs a multi-layered network structure to learn intricate relationships between inputs and outputs [19]. However, ANN algorithms typically require substantial training data to avoid overfitting and have stringent requirements for the quantity of training data as well as a strong reliance on factor independence. LightGBM enhances model prediction performance through gradient optimization but is susceptible to noise and outliers; moreover, its high model complexity may lead to overfitting [20]. These methods have constraints in elucidating the degree of influence exerted by independent variables on dependent variables, making them unsuitable for analyzing the influencing factors of RVP and their impact. Random Forest (RF), an ensemble learning method, improves prediction accuracy by constructing multiple decision trees and using voting mechanisms [21]. RF can effectively handle numerous features and classification problems while exhibiting high resilience towards noise and missing values. Additionally, RF evaluates model performance through Out-of-Bag (GINI-OOB) estimation, effectively mitigating the risk of overfitting. RF has been extensively applied across various domains such as finance [22], healthcare [23], climate change analysis [24], and image feature recognition [25] due to its broad applicability potential alongside practical value.

The objective of this study is to propose an RF-based RVP assessment model and investigate the key factors influencing RVP. Firstly, the RVP indicator system was constructed using Wuhan as a case city. In order to quantitatively assess RVP, this paper employs a dynamic evaluation method called the Fuzzy Comprehensive Evaluation-Attribute Hierarchy Model (FCE-AHM), which is experimentally validated using data from the 2022 Wuhan Social Satisfaction Survey. By integrating qualitative and quantitative analysis, the FCE-AHM method accurately determines the weights of various indicators [26], thereby establishing a comprehensive RVP evaluation system. Moreover, this paper employs the GINI index and OOB error of RF to identify the significance of different indicators [27]. The GINI index can pinpoint the most important variables for RVP, while the OOB error validates their actual contribution and performance in relation to RVP. Furthermore, coupling analysis using the Lagrange multiplier method allows for a deeper understanding of each variable’s role in shaping RVP. These methodologies have been successfully applied in urban planning [28], real estate, public policy, and consumer behavior research, offering novel perspectives and approaches to comprehending urban resident’s value perception.

Wuhan, a pivotal city in central China and one of the pilot cities for the “urban physical examination” [29,30], has been chosen as the focal point of this study. The emphasis is on exploring the role of RVP in fostering urban sustainability. By examining resident’s satisfaction levels regarding essential urban services such as education, healthcare, transportation, and environmental protection, we can gain insights into how these services influence resident’s quality of life—a crucial aspect for effective urban management and policy formulation [31]. Through a comprehensive analysis of resident’s value perceptions, it becomes feasible to allocate urban resources more rationally [32]. Furthermore, investigating resident’s value perceptions contributes to enriching theoretical frameworks within fields like urban sociology and social psychology while providing novel perspectives for urban research. Ultimately, it equips urban planners, policymakers, and managers with practical tools and strategies to promote sustainable development in cities.

The paper is structured as follows: The Section 2 delineates the indicator system for constructing RVP and discusses the key factors influencing RVP, providing a comprehensive analysis of the formation mechanism of RVP. Section 3 elaborates on the principles and formulas of the FCE-AHM comprehensive evaluation model and the GINI-OOB coupled factor mining model utilized in this study. Section 4 analyzes prominent factors influencing RVP using 2022 survey data from Wuhan. In Section 5, feasible recommendations for enhancing the RVP in Wuhan City are provided based on the results of data analysis. Finally, Section 6 summarizes research findings and provides an outlook on future research directions regarding resident’s value perception.

2. Materials and methods

2.1. RVP index system construction

In the context of rapid urbanization and economic development, there has often been a predominant focus on advancing the economy, while the well-being of the residents who are supposed to benefit from it is frequently overlooked [33]. Dempsey et al. [34] introduce a model of “Urban Social Sustainability”, which examines the relationship between economic development and resident’s well-being from a social perspective. Consequently, studying RVP becomes immensely important as it provides valuable insights into how residents perceive the benefits of urban development. From a social sustainability viewpoint, Xu et al. [35] examined the social well-being of urban residents from various dimensions, emphasizing social factors such as community cohesion, social inclusion, social equity, and quality of life. They also proposed the components of RVP, which include crucial aspects like ecological livability, health and comfort, and convenient transportation. These factors collectively shape individual's overall experience and satisfaction with their living environment. Understanding these elements fosters a more resident-centered approach to urban development, ensuring that growth aligns with the goal of improving the quality of life for city dwellers. Ecological livability encompasses fresh air, tree-lined streets, and abundant natural resources. Residents value the surrounding green spaces, water quality, and the health of ecosystems [36]. Ecologically livable communities not only benefit individual physical health but also contribute to an enhanced overall quality of life. Additionally, health and comfort are other critical components of RVP. A healthy and comfortable living environment considers factors such as housing structure, maintenance of community infrastructure [37], education [38], and elderly care [39], as these directly influence resident's physical and psychological well-being. The availability of convenient transportation within a community enables residents to easily access their workplaces, commercial areas, and other key destinations, thereby improving the convenience of daily life. Convenient transportation includes the accessibility and quality of public transport services, road conditions, and pedestrian and cycling infrastructure [36]. A well-developed transport network not only saves time and money but also enhances the overall accessibility of the community. To summarize, **Table 1** provides a quantified indicator system for RVP.

Table 1. RVP index system construction.

Criterion layer	Primary indicator	Secondary indicator	Reference
Resident Value Perception (L)	Ecologically livable (L_1)	Open space (L_{11})	[37,40]
		Water-related ecosystem (L_{12})	[41]
		Air pollution (L_{13})	[36,42]
		Population density (L_{14})	[40,43]
		Building height (L_{15})	[44]
		Park accessibility (L_{16})	[36]
		Noise pollution (L_{17})	[36]
		Water pollution (L_{18})	[45]
	Health and comfort (L_2)	Integrated community (L_{21})	[38]
		Proximity marketing (L_{22})	[37]
		Shopping mall (L_{23})	[37]
		Senior dining services at communities (L_{24})	[39]
		Universal preschool (L_{25})	[38]
		Community health center (L_{26})	[37]
		Community sports facilities (L_{27})	[37]
		Community charging stations (L_{28})	[46]
		Community infrastructure maintenance (L_{29})	[37]
		Community event organization (L_{210})	[37]
		Neighborhood relations (L_{211})	[47]
		Housing quality and housing maintenance level (L_{212})	[38]
		Renovation in old communities (L_{213})	[48]

Table 1. (*Continued*).

Criterion layer	Primary indicator	Secondary indicator	Reference
	Accessibility in transport (L_3)	Walkable environments (L_{31})	[38,49]
		Cycling environment (L_{32})	[49]
		Bus punctuality (L_{33})	[49]
		Public transit transfer(L_{34})	[38]
		Rail transit station area (L_{35})	[37]
		Road traffic flow (L_{36})	[49]
		Home parking convenience (L_{37})	[49]
		Commuting time (L_{38})	[38,49]

2.2. RVP influence factor

The RVP is influenced by various factors such as urban safety resilience, aesthetic characteristics of the cityscape, inclusiveness and diversity within the community fabric as well as cleanliness and orderliness in an urban setting along with its innovative vitality [16]. Urban safety resilience has a direct impact on resident's sense of security and their overall quality of life. This includes aspects like emergency response systems within cities to tackle unforeseen situations or natural calamities along with ensuring adequate public safety facilities are available [33]. Moreover, cities that possess distinct aesthetic features have the potential to instill cultural pride among their inhabitants while also enhancing their overall image which further encourages active participation in this exceptional living environment [35]. Simultaneously, urban areas must accommodate residents from diverse cultures and backgrounds, fostering social integration and the coexistence of diversity [36]. Considering the needs of various groups in urban planning fosters a just and equitable social environment. The cleanliness and orderliness of cities form the foundation for human habitation. Sustaining the tidiness and organization of urban spaces can provide inhabitants with a habitable living environment [37]. Lastly, the innovation vitality of cities directly correlates with their economic development and resident's quality of life. A city imbued with innovation vitality can attract the growth of high-tech industries and creative sectors [38], offering residents increased job opportunities as well as a richer array of cultural and entertainment activities, thereby promoting sustainable urban development. The summarized table illustrating factors influencing RVP is presented in **Table 2.**

Table 2. RVP influence factor.

Criterion layer	Primary indicator	Secondary indicator	Reference
RVP influence factor	Urban safety resilience (K_1)	Public safety (K_{11})	[50]
		Traffic order (K_{12})	[50]
		Fire hazard safety (K_{13})	[50]
		Emergency evacuation shelter (K_{14})	[37,50]
		Hospital waiting times (K_{15})	[50]
		Urban flooding (K_{16})	[50]
		Responses to natural disasters (K_{17})	[50]

Table 2. (*Continued*).

RVP influence factor	Urban safety resilience (K_1)	Safety accident management (K_{18})	[50]
	Urban landscape character (K_2)	Landmark building (K_{21})	[51]
		Cultural facility (K_{22})	[51]
		Preservation of historic districts (K_{23})	[52]
		Adaptive reuse and restoration of heritage buildings (K_{24})	[51,52]
		Tourist appeal (K_{25})	[53]
	Urban diversity and inclusivity (K_3)	Housing price inequality (K_{31})	[50,54,55]
		Rental affordability (K_{32})	[54]
		Regulation and professional in the rental housing market (K_{33})	[54]
		Levels of migrant-friendliness (K_{34})	[56]
		Care for vulnerable groups (K_{35})	[50,57]
		Minimum living standard guarantee (K_{36})	[58]
		Affordable housing development (K_{37})	[59]
		Shantytown and urban village regeneration (K_{38})	[57]
		Occupancy of tactile paving (K_{39})	[60]
		Ramp installation (K_{310})	[61]
	Urban governance (K_4)	Community waste sorting (K_{41})	[62]
		Property management (K_{42})	[63]
		Street cleanliness (K_{43})	[64]
		Manhole cover detection (K_{44})	[65,66]
		Vertical pole management (K_{45})	[67]
		Streetlight management and maintenance (K_{46})	[68]
		Parking management (K_{47})	[69]
		Management and installation of street signs (K_{48})	[70]
		Emergency Planning for water and Power Outages (K_{49})	[71,72]
	Urban innovation vitality (K_5)	Attracting talent (K_{51})	[73]
		Employment opportunities (K_{52})	[74]
		Market environment (K_{53})	[75]
		Technological innovation (K_{54})	[76]
		Attracted young adults (K_{55})	[73]
		Inclusive finance (K_{56})	[75]

2.3. RVP mechanism analysis

RVP includes three main dimensions: ecological livability, health and comfort, and convenient transportation. These dimensions are influenced by various indicators such as urban innovation vitality, cleanliness, and orderliness, as well as safety resilience. A schematic diagram that illustrates the mechanism of influence is presented in **Figure 1**.

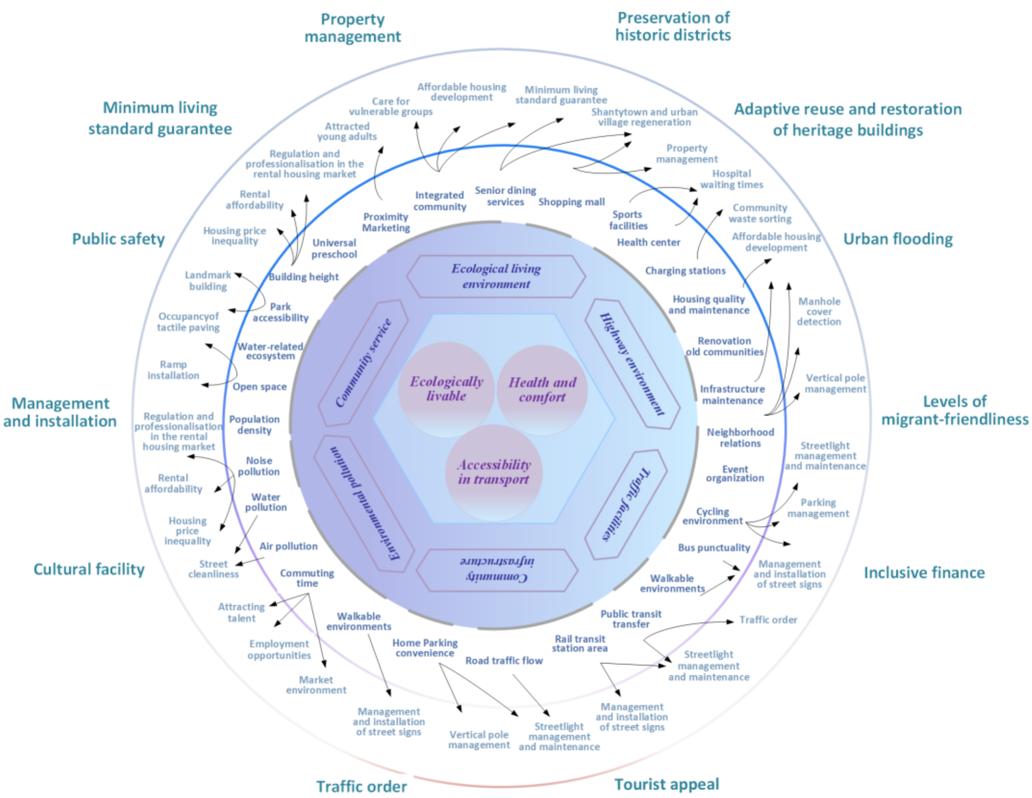


Figure 1. RVP mechanism.

i. The assessment of a city's ecological environment should consider the direct influence of its innovation vitality [77]. Cities with high levels of innovation vitality are more likely to adopt green technologies and sustainable development strategies, thereby promoting environmental protection and ecological balance. Additionally, the cleanliness and orderliness of a city serve as indicators of its proficiency in urban management and planning, exerting positive influences on ecological livability [78]. A clean and well-organized environment contributes to the enhancement of air and water quality, thereby fostering a more robust ecological milieu. Simultaneously, cities equipped with safety resilience are better equipped to withstand natural disasters and environmental fluctuations, thus bolstering ecosystem stability. The incorporation of green infrastructure and the establishment of ecological buffer zones within urban areas can augment ecological resilience while mitigating disaster risks.

ii. The vitality of urban innovation has a profound impact on urban planning and healthcare services, promoting health and well-being [79]. Innovative medical technology and healthcare services have the potential to enhance the quality of life for urban residents. A clean and organized urban environment plays a crucial role in preventing environmental pollution, mitigating the adverse effects of air and water pollution on resident's health, thereby creating a more comfortable living space [80]. Safety-resilient cities are better equipped to respond effectively to emergency medical situations and public health crises, fostering resident's sense of security in an urban setting.

iii. Urban innovation drives the advancement of transportation technology and intelligent transportation systems, thereby enhancing transportation efficiency and convenience [79]. Furthermore, the cleanliness and orderliness of a city directly impact the seamless functioning of its transportation system [81]. Effective urban planning and road management can alleviate traffic congestion and improve transportation convenience. Cities that prioritize safety resilience are better equipped to address transportation challenges and emergencies, consequently reducing traffic accidents.

3. Methodology

The objective of this article is to develop a predictive model for the RVP index. Firstly, prior to constructing the model, we conducted a survey to ascertain resident's perception of the relative importance of various value indicators, thereby establishing an evaluation index system for the RVP index. Secondly, we employed the AHM method which calculates indicator weights based on their hierarchical relationships [82]. Subsequently, we utilized the fuzzy comprehensive evaluation method to aggregate the weighted scores of each indicator and derive the final RVP index. Furthermore, after reviewing relevant literature and data, factors influencing RVP were identified and assessed using the GINI-OOB methodology. In this study, Wuhan will be used as the primary research subject. The scoring opinions in the urban health evaluation are inherently vague due to the use of an estimation system, classifying the data as fuzzy. Therefore, employing the FCE method effectively mitigates the challenges posed by such fuzzy data. The evaluation process is twofold, requiring consideration of both resident's subjective perceptions and the influence of objective information entropy. Additionally, the GINI-OOB method is adopted because traditional regression algorithms struggle to explain the impact of multidimensional factors on RVP. In contrast, deep learning offers a robust ability to uncover the intrinsic relationships and associations between data. The entire framework is illustrated in **Figure 2.**

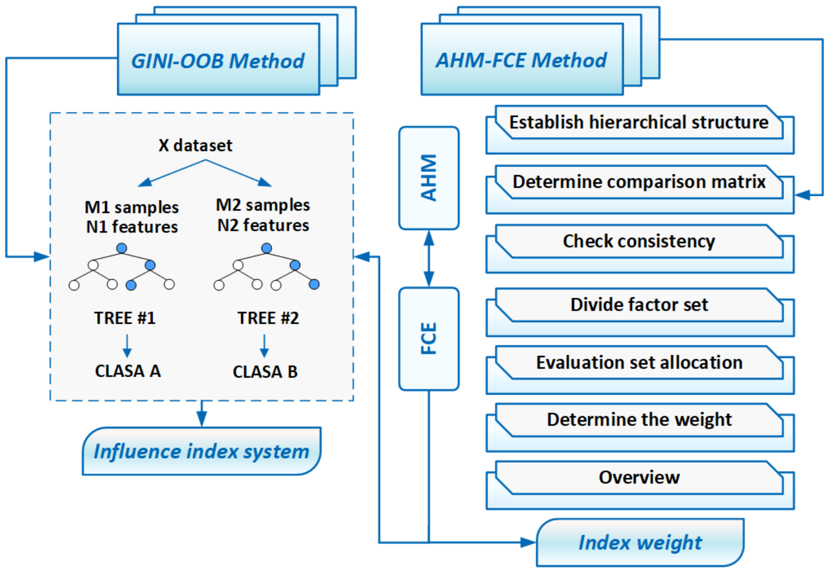


Figure 2. RVP computational frameworks.

3.1. FCE-AHM method

The fuzzy comprehensive evaluation method is a mathematical approach used to handle fuzzy information and multi-factor decision-making. Its main principle is based on fuzzy set theory, integrating various fuzzy factors, information, and weights to support decision-making [83]. The advantages of FCE include its effectiveness in dealing with incomplete information and fuzziness, allowing uncertain factors to be included in decision analysis. It can also comprehensively consider multiple factors and information sources, providing more comprehensive decision results.

The steps of FCE are as follows:

Step 1: Establish a multi-level evaluation indicator structure

Firstly, it is imperative to identify the factors that influence RVP and establish a comprehensive set of relevant variables. Constructing a rational evaluation indicator system constitutes a pivotal step in developing the RVP framework. This indicator system typically encompasses three layers: the goal layer, the criterion layer, and indicator layer. Assuming we designate the evaluation indicator system for RVP as *K,* each constituent of *K* signifies a factor that exerts an impact on RVP, as shown in Equations (1) and (2).

$$K = \{K_1, K_2, \ldots, K_n\} \tag{1}$$

$$K_n = \{k_{n1}, k_{n2}, \ldots, k_{nm}\} \tag{2}$$

The indicator system referred to as *K* in this section, influences RVP. $K_1, K_2, \ldots, K_n$ represents the factors within set *K* that impact the standard layer, while representing the factors within the standard K_n that affect the index layer. The initial part of this section establishes the indicator system.

Step 2: Determine evaluation criteria and levels

The second step involves creating an annotation set that encompasses descriptions of diverse potential evaluation outcomes for the object under evaluation. The annotation set *L* can be represented by the Equation (3). It is presumed that there are *m* factors capable of influencing the assessment results.

$$L = \{l_1, l_2, \ldots, l_m\} \tag{3}$$

In this section, $l_i (i = 1,2, \ldots, m)$ represents the possible evaluation results.

Step 3: Calculate indicator weights

Balancing the importance of different indicators is a crucial step in evaluating the RVP index. The allocation of weights essentially reflects the relative significance of each indicator and directly impacts the evaluation outcomes. This study employs the AHM to determine the weights assigned to each indicator within the indicator system. AHM inherits the advantages of the Analytic Hierarchy Process (AHP), while offering simplicity and convenience in terms of calculation and application compared to AHP [84]. AHM eliminates the need for computing eigenvectors or consistency checks, thereby avoiding extensive calculations, making it widely applicable across various decision-making scenarios.

Considering that most indicators influencing RVP are qualitative and cannot be directly quantified, it is necessary to transform them into measurable indicators for assessment purposes. Following the established RVP evaluation indicator system, let

P denote the comprehensive evaluation objective of RVP; K denotes a set consisting of primary evaluation indicators referred to as $K = \{K_1, K_2, \dots, K_n\}$; K_n denotes a set consisting of secondary evaluation indicators referred to as $K_n = \{k_{n1}, k_{n2}, \dots, k_{nm}\}$.

In the AHM method, the primary task in establishing the attribute judgment matrix is to determine the relative importance levels among various evaluation indicators. **Table 3** presents a specific scale and its corresponding meanings, using the Saaty scale as a reference.

Table 3. Saaty scale.

Importance level	**a_{ij} scale value**
Factors *i* and *j* are equally important.	1
Factor *i* is slightly more important than factor *j*.	3
Factor *i* is moderately more important than factor *j*.	5
Factor *i* is significantly more important than factor *j*.	7
Factor *i* is extremely more important than factor *j*.	9
Factor *i* is slightly less important than factor *j*.	1/3
Factor *i* is moderately less important than factor *j*.	1/5
Factor *i* is significantly less important than factor *j*.	1/7
Factor *i* is extremely less important than factor *j*.	1/9
Equally important between adjacent scale values.	2, 4, 6, 8
Equally unimportant between adjacent scale values.	1/2, 1/4, 1/6, 1/8

For a scenario with n factors, according to the Saaty scale and expert scoring method, a judgment matrix of order n can be generated, denoted as matrix $A = (a_{ij})_{n\times n}$. In this matrix, a_{ij} represents the importance value of factor i relative to factor j in achieving a specific goal. The comparison judgment matrix A should satisfy Equation (4):

$$\begin{cases} a_{ij} > 0 \\ a_{ii} = 1 \\ a_{ji} = 1/a_{ij} \\ i \neq j, 1 \leq i \leq n, 1 \leq j \leq n \end{cases} \tag{4}$$

According to the AHM method, a matrix P of order n, called the attribute judgment matrix, can be constructed, composed of relative attributes p_{ij}. These relative attributes p_{ij} can be determined by the values of scale a_{ij}, with the specific conversion formula detailed in calculation Equation (5).

$$p_{ij} = \begin{cases} \dfrac{2k}{2k+1}, a_{ij} = k, i \neq j \\ \dfrac{1}{2k+1}, a_{ij} = \dfrac{1}{k}, i \neq j \\ 0.5, a_{ij} = 1, i \neq j \\ 0, a_{ij} = 1, i = j \end{cases} \tag{5}$$

In Equation (5), k is a positive integer greater than or equal to 2. Based on the above, the attribute judgment matrix P can be determined.

The relative attribute weights are represented as in Equation (6):

$$W_{K_i}^{'} = \frac{2}{n(n-1)} \sum_{j=1}^{n} p_{ij}, i = 1,2,\ldots,n \tag{6}$$

The value of n in Equation (6) represents the number of sub-indicators that fall under the same parent indicator. Once the weights for each relative attribute are determined, it becomes possible to calculate composite weights.

$$W_{AHM} = W_{BAij}^{'} \times W_{CBij}^{'} \tag{7}$$

In Equation (7),W_{AHM} represents the relative weights of each factor with respect to the target P in the secondary indicators K_i, whileW_{BA}'represents the relative weights of each factor with respect to the target P in the primary indicators $K. W_{CB}'$ denotes the relative weights of each factor with respect to the primary indicators K in relation to the secondary indicators K_i.

Step 4: Determine the fuzzy evaluation matrix

The relationship between evaluation indicators and evaluation sets is represented by the degree of membership, which can be defined as the proportion of experts who assign a specific RVP index score to the total number of experts. Assuming there is a sub-evaluation q_{ij} between k_i and l_i, the evaluation result for k_i can be expressed as Equation (8):

$$Q_i = \{q_{i1}, q_{i2}, \ldots, q_{in}\} \tag{8}$$

The fuzzy evaluation Matrix (9) can be derived by calculating the assessment results for each indicator based on the evaluation indicator system and criteria, where Q_i represents the assessment outcome of factor K_i.

$$Q = \begin{bmatrix} Q_1 \\ Q_2 \\ \vdots \\ Q_n \end{bmatrix} = \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1k} \\ q_{21} & q_{22} & \cdots & q_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ q_{n1} & q_{n2} & \ldots & q_{nk} \end{bmatrix} \tag{9}$$

Step 5: Calculate the comprehensive assessment score

According to Equation (9), the weight vector and fuzzy evaluation matrix can be combined for result calculation. Once continuous evaluation results are obtained from both the indicator layer and standard layer, an overall perception index evaluation vector H can be generated. H can be expressed as Equation (10). To derive the final perception index evaluation value, it is necessary to aggregate and integrate the fuzzy vectors by applying a weighted average based on membership.

$$\begin{aligned} \mathrm{H} = W_{AHM} \times Q = (w_{AHM1}, w_{AHM2}, \ldots, w_{AHMn}) \times \begin{bmatrix} q_{11} & q_{12} & \cdots & q_{1k} \\ q_{21} & q_{22} & \cdots & q_{2k} \\ \vdots & \vdots & \vdots & \vdots \\ q_{n1} & q_{n2} & \cdots & q_{nk} \end{bmatrix} \\ = (h_1, h_2, \ldots, h_k) \frac{\partial y}{\partial x} \end{aligned} \tag{10}$$

$$C = H \times L^T \tag{11}$$

In Equation (11), C denotes the ultimate RVP index.

3.2. GINI-OOB-RF method

3.2.1. RF method

RF is an ensemble learning method that constructs multiple decision trees and integrates them into a robust model, offering efficient classification and regression capabilities, as well as evaluating feature importance [85]. The principle of RF relies on the ensemble of decision trees, where the optimal split at each node is determined by randomly sampling training data and features. Ultimately, a comprehensive decision is made through voting or averaging. This inherent randomness mitigates over fitting risks while enhancing the generalization ability of the model. In the schematic diagram, multiple decision trees are built in parallel, and the final prediction result is obtained through voting or averaging, exemplifying the concept of ensemble in RF. The randomness within each decision tree manifests itself in bootstrapping sampling of training samples and features to improve overall model robustness. The workflow of RF is shown in **Figure 3**.

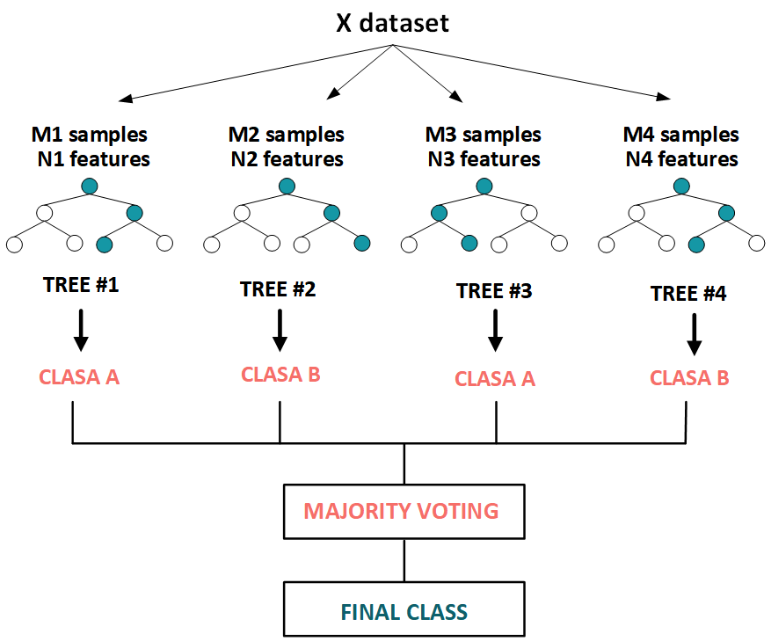


Figure 3. RF flow chart.

3.2.2. GINI method

The GINI index is incorporated into decision tree algorithms, specifically the Classification and Regression Trees (CART) algorithm, in the field of machine learning. Within the context of decision trees, the GINI index serves as a metric for assessing dataset purity by evaluating class distribution among samples [85]. During decision tree construction, features are selected based on their ability to minimize the GINI index for node splitting, thereby generating a tree model with superior generalization performance.

The GINI index is utilized during the process of node splitting in decision trees to assess the splitting capability of each feature. Features with lower GINI index values are selected for splitting in order to enhance the purity of the child nodes. Additionally, the GINI index guides the growth process of decision trees by determining how to partition the dataset at each node until meeting the stopping criteria.

Utilizing Variable Importance Measures (VIM) to quantify the significance of variables, the GINI index is denoted as *GI*. Assuming there are *K* features $M_1, M_2, M_3, \ldots, M_K$, T decision trees, and *A* categories, we now need to compute the GINI index scores $VIM_K{}^{(Gini)}$ for each feature M_K.

$$GI_y{}^{(i)} = \sum_{a=1}^{|A|}\sum_{a'\neq a} x_{ya}{}^{(i)}\, x_{ya'}{}^{(i)} = 1 - \sum_{a=1}^{|A|}\left(x_{ya}{}^{(i)}\right)^2 \; x \in R \quad (12)$$

The number of categories represented by *A* in Equation (12). Additionally, x_{ya} denotes the proportion of category *a* within node *y*. The significance of feature M_K at node *y* in the *i*-th tree, referring to the change in GINI index before and after branching at node *y*, can be quantified as follows:

$$VIM_{ky}{}^{(Gini)(i)} = GI_y{}^{(i)} - GI_s{}^{(i)} - GI_t{}^{(i)} \quad (13)$$

The GINI indices of the two new nodes after branching are denoted as$GI_s{}^{(i)}$and$GI_t{}^{(i)}$in Equation (13).

The importance of feature M_K in the *i*-th tree, which occurs in the set of nodes *Y*. The calculation is presented in Equations (14)–(16).

$$VIM_y{}^{(Gini)(i)} = \sum_{y\in Y} VIM_{ya}{}^{(Gini)(i)} \quad (14)$$

Assuming there are I trees in the RF, then

$$VIM_y{}^{(Gini)(i)} = \sum_{i=1}^{I} VIM_y{}^{(Gini)(i)} \quad (15)$$

Finally, standardize all the obtained importance scores.

$$VIM_Y{}^{(Gini)} = \frac{VIM_y{}^{(Gini)}}{\sum_{y'=1}^{y} VIM_{y'}{}^{(Gini)}} \quad (16)$$

3.2.3. OOB method

In a RF, multiple decision trees are created using a bootstrapping method with replacement. Each sampling generates a bootstrap sample, and due to the inherent nature of replacement, certain training samples may not be selected in a specific sampling iteration, resulting in the formation of OOB data [86].

The performance of the RF model can be evaluated using OOB samples. These samples were not used in constructing a specific decision tree, so they serve as a validation set to estimate the generalization performance of the model without needing an additional validation set [87]. Furthermore, OOB data allows for assessing feature importance by observing their contribution to splits during each decision tree construction process. This helps estimate which features contribute most significantly to the overall model performance. By utilizing OOB data for model evaluation, it becomes possible to detect whether the model is overfitting to the training data.

The decision trees in the RF use training samples to construct the tree and evaluate the OOB prediction error rate. Afterwards, observations of variable M_K are randomly permuted, resulting in a rebuilt tree and calculation of the permuted OOB prediction error rate. Finally, the difference between these two OOB error rates is standardized and computed as permutation importance for variable M_K. This process is repeated across all trees to obtain comprehensive permutation importance for variable M_K.

Ultimately, averaging across all trees provides the overall permutation importance $VIM_Y^{(OOB)}$ for variable M_K in the x-th tree of the RF as shown in Equation (17).

$$VIM_y^{(OOB)} = \frac{\sum_{s=1}^{n_s'} O(T_s = T_s^x)}{n^x} - \frac{\sum_{s=1}^{n_s'} O(T_s = T_{s,\pi_y}^x)}{n^x} \tag{17}$$

where n_x represents the number of samples in the OOB data for the x-th tree, $O(x)$ is an indicator function that takes a value of 1 if two values are equal and 0 otherwise. ${T_s}^x \in \{0,1\}$ denotes the true value of the s-th sample, ${T_s}^x \in \{0,1\}$ represents the prediction of the s-th sample by the x-th tree before random permutation, and ${T_{s,\pi_y}}^x \in \{0,1\}$ signifies the prediction after random permutation. If variable y does not appear in tree x, it is denoted as $VIM_j^{(OOB)} = 0$.

The permutation importance $VIM_Y^{(OOB)}$ of variable MK in a RF is defined as illustrated by Equation (18). The variable k represents the number of classification trees included in a RF.

$$VIM_Y^{(OOB)} = \frac{\sum_{x=1}^{n} VIM_{xy}^{(OOB)}}{k} \tag{18}$$

3.2.4. Lagrange multiplier method

The Lagrange multiplier method can incorporate multiple constraints into the objective function to comprehensively consider each constraint [4]. After calculating the GINI and OOB indices for each variable, the GINI and OOB indices are used as constraints. The Lagrange multiplier method is employed to couple the GINI and OOB indices and integrate them into the variable importance evaluation system to further optimize the degree of variable influence. The decoupled importance is finally obtained as shown in Equation (19).

$$VIM_x = \frac{\left(VIM_y^{(OOB)} {VIM_y}^{(Gini)}\right)^{0.5}}{\sum_{x=1}^{n}\left(VIM_y^{(OOB)}, {VIM_y}^{(Gini)}\right)^{0.5}} \tag{19}$$

The influence of variables on the perception system of Wuhan's urban living environment can be determined using different evaluation indicators.

3.3. Setting of inspection criteria

In order to comprehensively evaluate the performance of the RVP system, this study employs three regression evaluation indicators: Mean Absolute Error (MAE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE). Statistical errors serve as a common method for assessing model prediction characteristics [88]. Without them, accurate measurement of the model's predictive capability would be impossible. Neglecting indicator testing when applying the model directly for practical applications may lead to failure in meeting prediction requirements [89]. Moreover, it would hinder comparisons with other model's performance, making it challenging to identify further directions for improvement and optimization. The formulas for evaluating these indicators are provided in Equations (20)–(22).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y_i - P_i)^2 \tag{20}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(Y_i - P_i)^2}{\sum_{i=1}^{N}(Y_i - \overline{Y}_i)^2} \tag{21}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_i - P_i}{Y_i}\right| \times 100\% \tag{22}$$

In Equations (20)–(22), Y_i and P_i respectively represent the observed values and predicted values.

The mean squared error (MSE) calculates the absolute value of the square difference between predicted and actual values, indicating a smaller MSE when the model's predictions are closer to the actual values. R^2 represents the ratio of regression sum of squares to total sum of squares, with an approaching value of 1 indicating effective explanation for target variable variability. The mean absolute percentage error (MAPE) measures average absolute percentage errors between true and predicted values, where a larger MAPE signifies greater error.

4. Results

4.1. Study area

The city of Wuhan (latitude 29°58′–31°22′ N, longitude 113°41′–115°05′ E) is the capital of Hubei Province in China and strategically located at the confluence of the Yangtze and Han rivers. It serves as a pivotal hub for politics, economy, culture, finance, and transportation within Hubei Province. Benefiting from its unique geographical advantage, Wuhan occupies a central position in China where nine provinces intersect. The historical roots of Wuhan can be traced back to the early to middle Neolithic period approximately 8000 to 6000 years ago when human settlements flourished amidst an intricate network of waterways [30].

As the capital and mega-city of Hubei Province, Wuhan holds the status of a sub-provincial city, occupying a distinctive position in central China. Designated as a 'central center city’ by the country, Wuhan is presented with abundant opportunities and prospects for its urban development [90]. As of 2022, the city’s permanent resident’s population reached 13.739 million, influenced by various factors such as its economy, culture, and education.

As the capital of Hubei Province, Wuhan exemplifies and represents the urban development status of the central region. Moreover, it has undergone rapid urbanization and economic transformation, grappling with similar challenges faced by other major cities such as traffic congestion and environmental pollution [90]. As one of China’s major megacities, Wuhan has a high population density, leading to traffic congestion, housing shortages, and unequal distribution of public services, all of which negatively impact resident’s quality of life and well-being. Although Wuhan has made progress in environmental governance, some areas still suffer from air pollution and declining water quality, affecting the comfort of living. Additionally, the uneven development of urban infrastructure, particularly the inadequate supply of educational and medical resources in new areas, further hampers the living experience of residents [29]. Therefore, studying Wuhan’s RVP can provide valuable insights into urban resident’s attitudes and perspectives when confronted with significant challenges. The surveyed sample area is depicted in **Figure 4**.

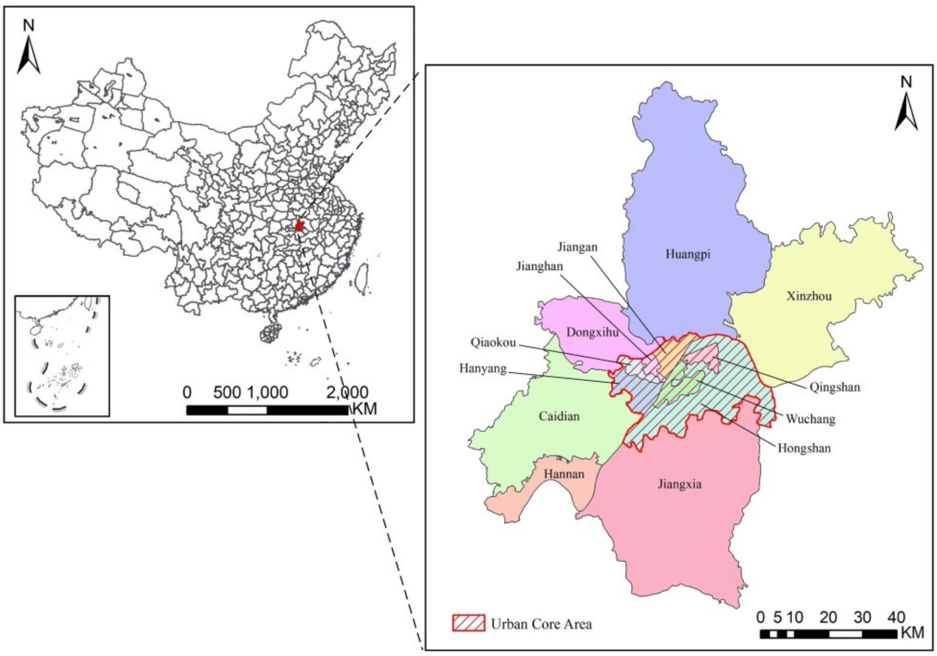


Figure 4. Geographical location of Wuhan City.

4.2. Data compilation

The data used in this study was obtained from the 2022 Urban Health Survey conducted in Wuhan. Three aspects of the questionnaire, namely ecological livability, health comfort, and transportation convenience, were selected based on constructed indicators. Residents of Wuhan provided ratings for 67 indicators on a scale ranging from 0 to 100, with higher scores indicating a greater perceived importance of the indicator. A total of 13,015 data points were initially collected, and after removing samples with missing values, 6976 valid data points remained. The findings are presented in **Figures 5** and **6** where the horizontal axis represents the indicators and different colors denote resident's satisfaction scores for each indicator.

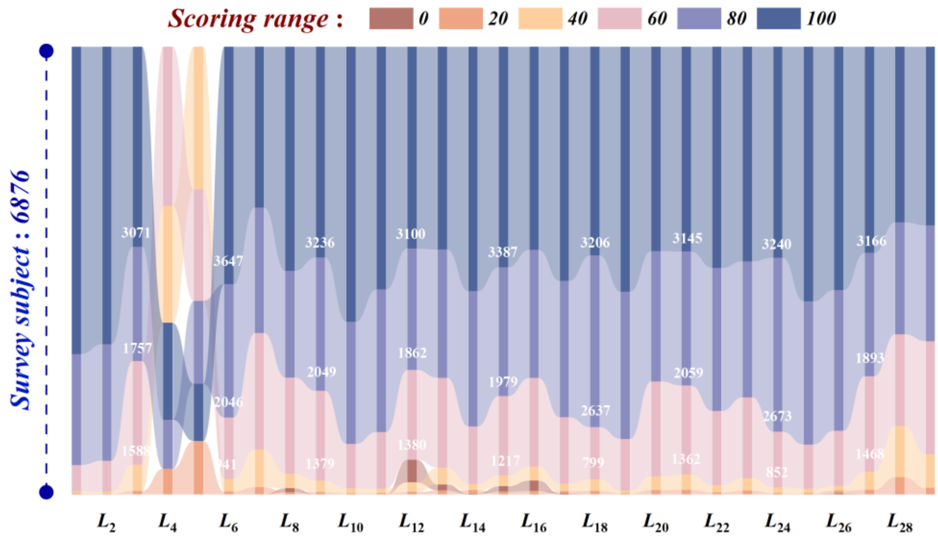


Figure 5. Statistics of RVP indicator scores.

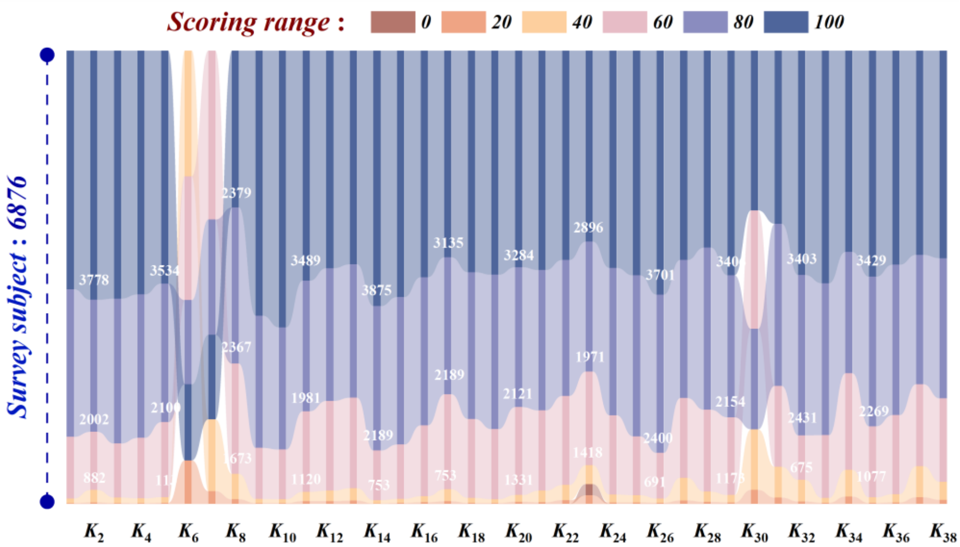


Figure 6. Statistical scoring of RVP indicator's impact factor.

The data reveals that the majority of indicators achieved scores of 80 or above, indicating a high level of overall satisfaction among Wuhan residents with these indicators. However, out of the 59 indicators examined, four received acceptability scores below 60: population density, building height, urban housing prices, and rents. This suggests that Wuhan's large population and elevated housing prices may contribute to a diminished quality of life and increased living stress. Furthermore, there were nine indicators with scores of zero; notably, elderly dining halls were rated as zero by 349 respondents which highlights the inadequate provision of such facilities in certain areas of Wuhan.

4.2. RVP calculation

4.2.1. Calculation of AHM weights

Table 4. RVP Indicator weights.

Primary indicator	WBA	Secondary indicator	WCB	WAHM
L1	0.1429	L11	0.1558	0.0223
		L12	0.0602	0.0086
		L13	0.0329	0.0047
		L14	0.1558	0.0223
		L15	0.1558	0.0223
		L16	0.0524	0.0075
		L17	0.3269	0.0467
		L18	0.0602	0.0086
L2	0.4286	L21	0.2012	0.0862
		L22	0.0846	0.0362
		L23	0.0846	0.0362
		L24	0.0433	0.0185
		L25	0.0365	0.0157
		L26	0.0957	0.0410
		L27	0.0336	0.0144
		L28	0.0309	0.0132
		L29	0.0336	0.0144
		L210	0.0309	0.0132
		L211	0.0309	0.0132
		L212	0.1950	0.0836
		L213	0.0993	0.0426
L3	0.4286	L31	0.1574	0.0675
		L32	0.1574	0.0675
		L33	0.0565	0.0242
		L34	0.0565	0.0242
		L35	0.0691	0.0296
		L36	0.1806	0.0774
		L37	0.0525	0.0225
		L38	0.2701	0.1157

To ensure the precise and realistic determination of indicator weights, we conducted interviews with a panel of 13 experts, including 7 professionals from the Urban Planning Bureau and 6 academic experts. These individuals possess extensive experience exceeding a decade in urban planning, community services, infrastructure development, and urban environmental protection within Wuhan. By consulting these aforementioned experts, an AHM weight matrix for the RVP independent indicators was formulated. The final calculation results for each independent variable's weight are presented in **Table 4**.

4.2.2. Quantify RVP

In the Python environment, we integrated the scoring results of various indicators in RVP to derive comprehensive scores for four main dimensions: Ecological livability (L_1), Health and comfort (L_2), Transport accessibility (L_3), and the overall RVP scoring index. A higher index value indicates better performance in a specific indicator, leading to a higher comprehensive evaluation. This approach allows for comparability among different indicators, facilitating comprehensive evaluation and comparative analysis. These scores provide a holistic understanding of regional conditions and serve as a scientific basis for development planning. The specific results are illustrated in **Figure 7**.

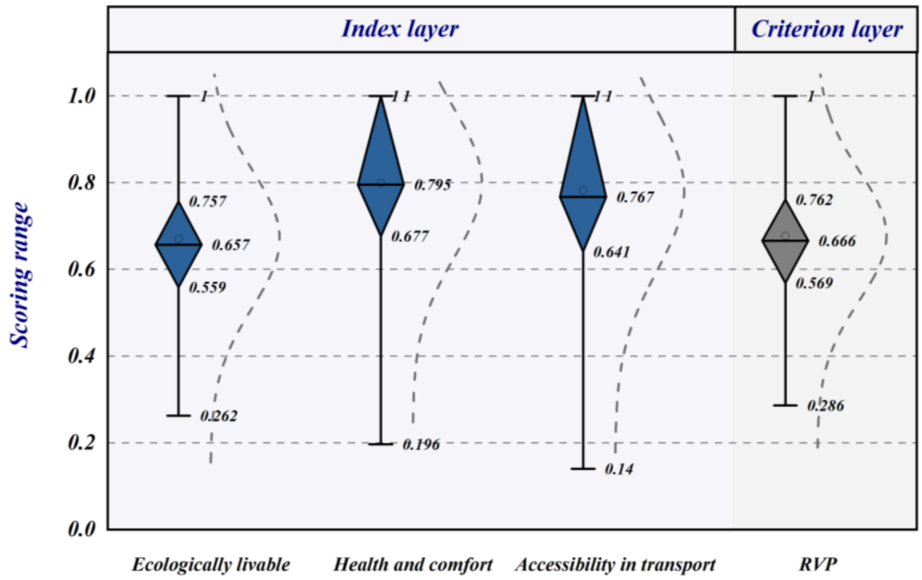


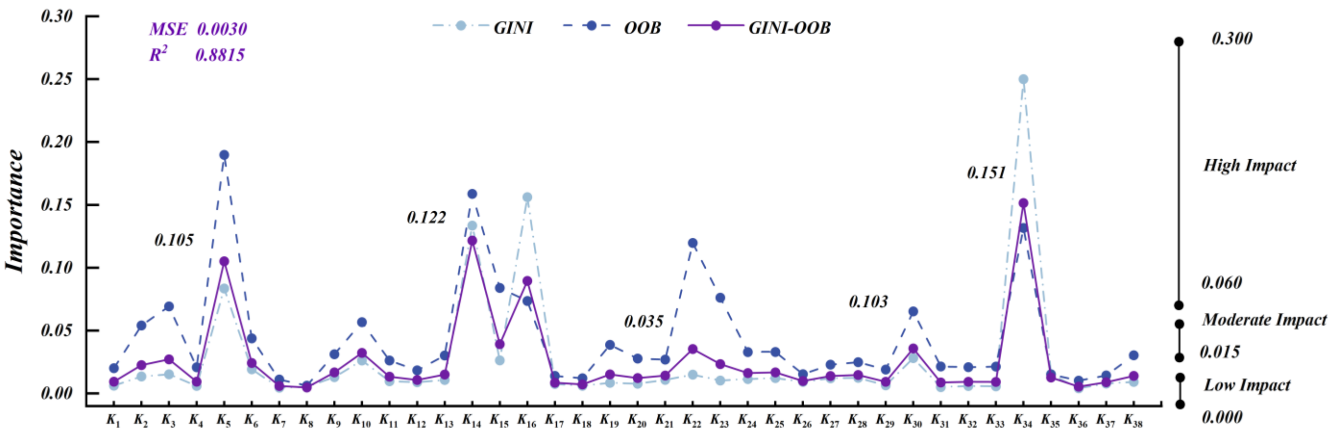
Figure 7. RVP index.

The comprehensive evaluation reveals that the average RVP index of Wuhan City is 0.666, indicating a relatively high overall satisfaction among residents with their living environment. Among the three sub-indicators, the average value of L_1 is 0.657, slightly lower than the overall RVP index, suggesting that although Wuhan City has made certain achievements in ecological construction, there is still room for improvement to further enhance resident's perception of ecological livability. The performance of indicators L_2 and L_3 stands out remarkably well, with average values of 0.795 and 0.767 respectively. It is worth noting that the box plots for these two indicators demonstrate an upper quartile coinciding with the maximum value of 1, indicating a higher proportion of evaluations reaching an index score of 1 in the survey. This data not only reflects significant accomplishments by Wuhan City in providing a healthy and comfortable living environment as well as convenient transportation services but also showcases citizen's exceedingly high satisfaction in these two aspects.

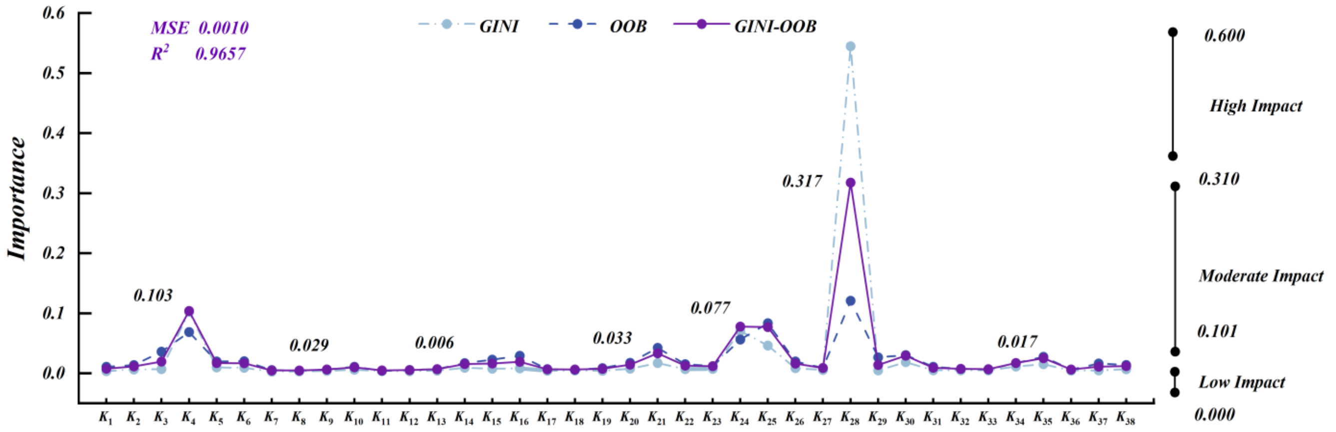
In conclusion, Wuhan City's efforts to improve urban health comfort and transportation convenience have been widely acknowledged by its citizens. However, to achieve more balanced and harmonious development, it is imperative for Wuhan City to strengthen ecological construction and environmental enhancement measures to further enhance resident's quality of life.

4.3. GINI-OOB method

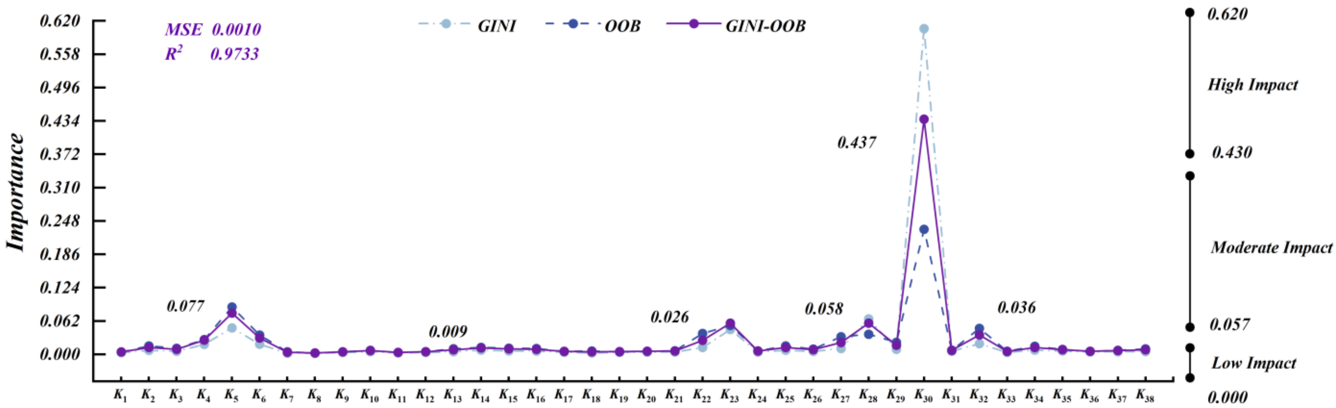
In this study, the RF algorithm was utilized to train and analyze the structure by adjusting parameters based on MSE and R^2. For feature selection, we employed the GINI index to determine the optimal split point of features. The GINI index is obtained by calculating the complement of the sum of squares of class sample proportions in the current node's sample set. Additionally, each tree's MSE was calculated using out-of-bag data, and an overall OOB error for RF was obtained by taking a weighted average of all tree's errors. Furthermore, we integrated the GINI index with OOB error using Lagrange multipliers to form GO metric. The results corresponding to each indicator are presented in **Figure 8a–c**, while those related to RVP are shown in **Figure 8d**. Through this coupling method, we can incorporate trends from GO metric and mitigate extreme data point's influence on data importance. The training results demonstrated that our model achieved a minimal MSE value approaching zero and a maximum R^2 value approaching 1. Specifically, our model attained an overall accuracy exceeding 0.9312 for R^2 while maintaining MSE below 0.0018.



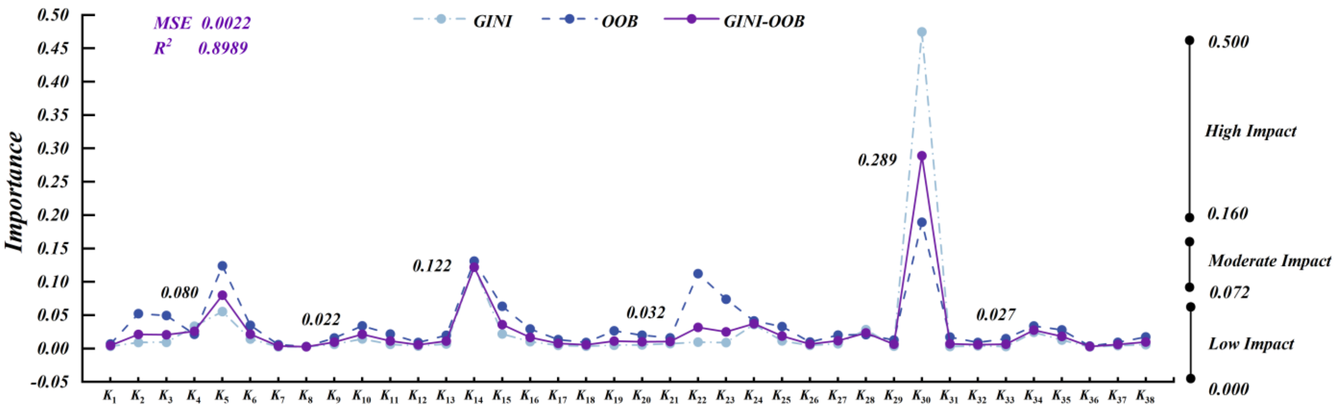
(a) Ecologically livable.



(b) Health and comfort.



(c) Accessibility in transport.



(d) Resident value perception.

Figure 8. Degree of influence of each indicator.

The impact of each indicator on Ecologically livable (L_1) is illustrated in **Figure 8a**, categorized into three ranges: 0~0.015 represents low impact; 0.015~0.060

indicates moderate impact, and values above 0.060 are considered high impact. Among all indicators, Employment opportunities (K_{34}) exhibit the most significant influence. Regions with abundant job opportunities tend to attract more residents, thereby driving economic development and social progress. Simultaneously, the distribution of job opportunities closely relates to urban planning and construction, emphasizing the importance of considering industrial development and employment markets [91]. Notably, the waiting time for outpatient services at Hospital waiting times (K_5), Housing price inequality (K_{14}), and Regulation and professional in the rental housing market (K_{16}) also demonstrate considerable impacts. Analysis reveals that regions providing convenient medical services, reasonable housing prices, and a standardized rental market can greatly enhance their ecological livability. Lastly, Safety accident management (K_8) have the lowest degree of impact; however, this does not imply that they do not affect ecological livability but rather suggests a relatively low occurrence rate or less attention from individuals towards safety accidents in the studied area. Nonetheless, safeguarding people's lives and property remains an important responsibility for governments and society.

The impact of each indicator on Health and comfort (L_2) is generally higher than that on L_1 and L_2, as shown in **Figure 8b**. This suggests that when assessing the overall livability of Wuhan City, health and comfort may hold greater significance compared to other factors. Notably, Vertical pole management (K_{28}) exerts a substantial influence on the level of health and comfort due to its ability to enhance the city's aesthetics, reduce visual pollution, and directly affect resident's physical and mental well-being [92]. Therefore, urban managers should prioritize the cleanliness and management of street skylines during urban infrastructure planning and maintenance. Additionally, Emergency evacuation shelter (K_4), Community waste sorting (K_{24}), and Property management (K_{25}) have a moderate impact on health and comfort. These indicators possess intricate relationships with health and comfort. For instance, emergency shelters provide safety assurance during emergencies while effective waste sorting practices along with good property management contribute to creating a clean and orderly living environment—crucial components for resident's healthiness and quality of life. The remaining indicators exhibit similar impacts on healthiness and comfort which implies that comprehensive balance should be achieved by considering multiple aspects when evaluating the healthiness and comfort of an area.

The results depicted in **Figure 8c** demonstrate that the factors exerting the most significant influence on Accessibility in transport (L_3) have a greater impact compared to those influencing L_1 and L_2, suggesting that residents perceive a convenient and efficient transportation system as having a more direct and substantial effect on their daily lives. Regarding transportation convenience in Wuhan, apart from Parking management (K_{30}), the effects of other indicators are generally similar. Effective management of motor vehicle and non-motorized vehicle parking can effectively alleviate traffic congestion and enhance road utilization efficiency, thereby directly enhancing resident's travel convenience. Furthermore, K_5 and Ramp installation (K_{23}) also exhibit notable impacts relative to other indicators. Comprehensive hospitals are typically situated in city centers or areas with high traffic volumes, attracting numerous patients, visitors, and medical staff who frequently commute to these facilities. Prolonged waiting times for hospital visits result in increased concentration of people and vehicles near hospitals, consequently impeding traffic flow smoothness. The strategic placement of curb ramps at intersections and crosswalks plays an essential role in managing traffic flow by mitigating conflicts between pedestrians/non-motorized vehicles and motor vehicles [93].

The trends depicted in **Figure 8a–c** are integrated in **Figure 8d** to present a comprehensive overview of the impact of each indicator on resident's perception of value. Among these indicators, K_5, K_{14}, and K_{30} exhibit the highest level of influence as evidenced by their combined GINI-OOB index of 0.4914. Notably, among them, parking management (K_{30}) has the most significant impact. The analysis reveals that residents hold exceedingly high expectations regarding convenience and quality of life in their daily routines. Specifically, an excessively long wait time for appointments not only results in congestion and higher noise levels in the waiting area which adversely affect patient's recovery but also directly impacts the perceived value of urban residents [94]. Additionally, high-density residential areas caused by overcrowding often experience elevated noise levels due to a dense population and heavy traffic which further influences resident's perceived value [95]. Poor parking management can lead to traffic congestion and frequent vehicle honking thereby increasing traffic noise and diminishing resident's quality of life [96]. Therefore, it is crucial to prioritize augmenting healthcare resources and optimizing hospital processes for reducing appointment waiting times; implementing housing subsidies along with market regulations for ensuring affordable house prices; and constructing additional parking facilities while promoting public transportation options as a means to alleviate parking difficulties. The individual impacts of other indicators may be relatively small, but they can still play a significant role in specific groups or circumstances that should not be overlooked. The average impact level across all indicators is 0.026, suggesting that while their individual effects may be limited on their own merits, their cumulative effect should not be disregarded. Therefore, it remains crucial to comprehensively enhance urban services and living environments, including improvements in acoustic surroundings, in order to effectively improve resident's quality of life and strengthen their sense of belonging with the city.

5. Discussions

Combining **Figure 8a**, it is evident that K_{34} exerts a significant influence. The presence of ample employment opportunities not only attracts population migration but also enhances the ecological livability of the region, thereby promoting economic and social development. Moreover, K_5, K_{14}, and K_{16} are key factors that reflect the crucial impact of accessible medical services, reasonable housing prices, and a regulated housing market on ecological livability. This finding aligns with the research results of Nikoofam et al. [97], underscoring the importance of these aspects in urban planning and policy-making for improving urban ecological livability. Given their substantial impact, prioritizing these issues will establish a solid foundation for enhancing ecological livability while simultaneously improving overall living standards for residents. Therefore, it is imperative to prioritize job market development in urban planning by creating more employment opportunities. Simultaneously, city managers should strive to enhance healthcare service systems to reduce waiting times for medical visits while ensuring reasonable housing prices and maintaining a regulated housing market.

The results depicted in **Figure 8b** demonstrate that the key determinants influencing health comfort include K_{28}, K_4, K_{24}, and K_{25}. These factors represent the significant impact of urban management and infrastructure development on resident's well-being. A meticulous analysis of **Figure 8b** reveals that these factors have a significant influence on health comfort across multiple dimensions. For example, proficient management of street aerial landscapes can enhance the city's aesthetics, reduce visual pollution, and directly affect resident's physical and mental health as well as their satisfaction with living conditions. Furthermore, providing emergency shelters ensures safety during unforeseen circumstances while efficient waste sorting and exemplary property management promote a clean and orderly living environment—all essential components contributing to resident's health and quality of life. On the other hand, the remaining factors have relatively minor effects on health comfort signifying that when evaluating the level of health comfort in an area, comprehensive balanced development requires consideration of multiple aspects. Therefore, it is recommended for Wuhan City to promptly implement policies encouraging and supporting street aerial landscape management to enhance urban aesthetics while simultaneously exploring other infrastructure and management measures aimed at comprehensively improving resident's levels of health comfort along with overall livability. This finding aligns with Zhao et al.'s research [98].

Based on the analysis presented in **Figure 8c**, notable disparities can be observed among the key determinants influencing transportation convenience. The influence of Parking management (K_{30}) on transportation convenience signifies resident's emphasis on efficient parking management systems, which not only effectively mitigates traffic congestion and enhances road utilization efficiency but also directly augments resident's travel convenience. This finding aligns with the research conducted by Wang et al. [99], highlighting the pivotal role of well-managed urban infrastructure in ensuring smooth traffic flow. Furthermore, both K_5 and K_{23} exhibit significant impacts on transportation convenience. This observation concurs with evidence from Wuhan, where comprehensive hospitals are typically situated in city centers or bustling areas, leading to increased gathering of people and vehicles due to longer medical appointment waiting times, thereby affecting traffic flow dynamics. Consequently, it becomes imperative to meticulously design roadside ramps at intersections and pedestrian crossings to minimize conflicts between pedestrians and motor vehicles while enhancing overall traffic safety and flow [100].

After analyzing **Figure 8d**, it becomes evident that K_5, K_{14}, and K_{30} are the three factors exerting the most significant influence on resident's perceived value. Notably, Parking management (K_{30}) exhibits the highest influence index in the graph, indicating a strong emphasis placed by residents on parking convenience. Effective parking management and ample parking facilities can not only alleviate traffic congestion but also enhance resident's travel efficiency and life satisfaction [100].

The importance of timely medical services is reflected through the significance of K_5. Prolonged waiting times for medical treatment not only impact patient's treatment outcomes but also have adverse effects on their mental well-being. Therefore, increasing medical resources and optimizing hospital processes assume paramount importance. The substantial impact of K_{14} underscores housing affordability's major influence on resident's life satisfaction. Ensuring reasonable housing prices through housing subsidies and market regulation can effectively mitigate economic pressure faced by residents while enhancing their overall quality of life [101].

In conclusion, urban administrators should enhance resident's quality of life by optimizing the job market, increasing healthcare resources, regulating housing prices, and improving infrastructure management. Specific measures include providing more employment opportunities, streamlining medical service processes, ensuring affordable housing prices, and strengthening parking management. If these measures are effectively implemented and managed with government policy support and efficient resource allocation [102], they will significantly improve the livability of cities while achieving comprehensive and sustainable development as well as enhancing resident's satisfaction with their lives.

6. Conclusions and limitation

6.1. Conclusions

The sustainable development of cities faces numerous obstacles, among which the inadequacy of RVP significantly hampers the rapid and sustainable progress of urban areas, as it plays a crucial role in enhancing the well-being of urban dwellers. To promote sustainable urban development, researchers and urban managers are dedicated to uncovering the fundamental factors that influence resident's value perception. Although existing research has provided valuable perspectives and methods for understanding RVP, these studies primarily rely on traditional factor analysis and basic data mining techniques, failing to fully exploit the advanced analytical capabilities offered by machine learning. In order to delve deeper into the factors influencing urban resident's value perception, this study proposes an innovative research framework and algorithm for RVP assessment. This framework integrates FCE-AHP and GINI-OOB methods. The main findings are as follows.

(1) The proposed method effectively identifies and quantifies the composite impact of natural environment, urban planning, social services, and economic conditions on urban resident's value perception. By utilizing machine learning technology, we can more accurately identify and evaluate the specific role played by these key factors in enhancing resident's life satisfaction and well-being. This approach not only provides empirical evidence for urban managers on how to enhance resident's value perception but also promotes the application of machine learning in urban research while offering a new perspective and technical means for comprehensively understanding complex mechanisms underlying resident's value perception in cities.

(2) The present study was conducted based on expert consultation and a thorough literature review, resulting in the development of a comprehensive system

comprising 29 specific indicators to quantitatively assess resident's perception of urban value. These indicators were meticulously categorized into three primary dimensions, ensuring a comprehensive understanding of resident's perception of urban quality. Through meticulous analysis, the study identified 38 key factors that significantly influence resident's perception of value, which were further classified into five distinct levels. At the macro level, core factors shaping resident's positive value perception encompassed the cleanliness and orderliness of the city, as well as its diversity and inclusiveness. On a micro level, crucial determinants directly impacting daily satisfaction and quality of life for residents included waiting time for outpatient services at comprehensive hospitals, acceptability of housing prices among residents, and issues related to parking facilities for both motorized and non-motorized vehicles.

(3) When dealing with RVP data, traditional factor analysis methods may encounter challenges such as multicollinearity, a limited ability to capture nonlinear relationships and interactions, as well as reliance on the assumption that data follows a normal distribution. To overcome these limitations, it is crucial to integrate machine learning techniques like the GINI-OOB algorithm. These algorithms excel at handling large and complex datasets while effectively identifying nonlinear relationships and interactions that uncover hidden patterns and trends influencing RVP. By utilizing these algorithms, researchers can gain a deeper understanding of the factors affecting RVP which in turn provides a more accurate and comprehensive scientific basis for urban planning and policy-making.

6.2. Limitations and future work

To enhance resident's sense of well-being and promote sustainable urban development, this study has developed an evaluation system for RVP and proposed a novel approach to analyze the specific impact of each indicator on RVP, aiming to comprehensively uncover the key factors influencing resident's perception of urban value. Although significant progress has been made in this study, future work needs to address several crucial issues.

The current study conducted a static analysis of the influencing factors of RVP in urban areas. However, it should be noted that the formation of RVP is a dynamic process that evolves over time, with causes and states changing across different stages of development. Therefore, future research should adopt dynamic analysis methods such as structural equation modeling (SEM) [103] or system dynamics modeling (SDM) [104] to delve into the interdependent relationships between human settlement perception and its influencing factors.

(1) This study did not incorporate spatial validation when applying machine learning or data mining techniques. Future research could consider integrating GIS technology to deepen the evaluation and analysis of human settlement perception. By integrating spatial and attribute data, GIS can enable real-time monitoring and prediction of resident's value perception while providing precise geographic information support for urban planning, thus facilitating sustainable urban development.

(2) When analyzing resident's value perception, this study primarily relies on survey data collected through questionnaires. However, it is important to acknowledge that relying solely on this single data source may not fully capture the complexity of resident's true sentiments and perceptions towards the city. Therefore, future studies should consider integrating multiple data sources. In particular, incorporating sentiment analysis can effectively capture resident's unstructured opinions and emotions expressed on social media platforms and other online channels, thereby supplementing and enriching traditional survey data. Additionally, combining macro-level statistical data such as economic growth, population mobility, and environmental indicators can provide a broader socio-economic context for understanding resident's value perception.

(3) While analyzing the influencing factors of resident's value perception in this study, it is essential to recognize that there might be limitations in interpreting the results due to potential omitted variable bias or endogeneity issues caused by unobserved confounding variables. To address these concerns in future research endeavors, employing propensity score matching (PSM) [105] method could be beneficial as it allows for a more rigorous analysis of causal relationships between variables while reducing the impact of endogeneity problems.

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References

1. Pincetl, S.; Gearin, E. The Reinvention of Public Green Space. Urban Geogr 2005, 26, 365-384, https://doi.org/10.2747/0272-3638.26.5.365.
2. Newman, P.; Kosonen, L.; Kenworthy, J. Theory of urban fabrics: planning the walking, transit/public transport and automobile/motor car cities for reduced car dependency. Town Plan Rev 2016, 87, 429-458, https://doi.org/10.3828/tpr.2016.28.
3. Liu, M.; Liu, J. Life Satisfaction Research-Quantitative Analysis Based on Wuhan City, In Proceedings of the 2020 International Conference on Big Data Economy and Information Management (BDEIM), Zhengzhou, China, 11-13 Dec 2020; pp. 109-111.
4. Han, W.; Jung, D.W.; Lee, J.; Yu, C. Determination of eigenvectors with Lagrange multipliers. J Korean Phys Soc 2021, 78, 1018-1022, https://doi.org/10.1007/s40042-021-00112-3.
5. Vorkinn, M.; Riese, H. Environmental Concern in a Local Context: The Significance of Place Attachment. Environ Behav 2001, 33, 249-263, https://doi.org/10.1177/00139160121972972.

6. Moudon, A.V.; Lee, C.; Cheadle, A.D.; Garvin, C.; Johnson, D.; Schmid, T.L.; Weathers, R.D.; Lin, L. Operational Definitions of Walkable Neighborhood: Theoretical and Empirical Insights. Journal of Physical Activity and Health 2006, 3, S99-S117, https://doi.org/10.1123/jpah.3.s1.s99.
7. Devine-Wright, P.; Howes, Y. Disruption to place attachment and the protection of restorative environments: A wind energy case study. J Environ Psychol 2010, 30, 271-280, https://doi.org/10.1016/j.jenvp.2010.01.008.
8. Williams, D.R.; Vaske, J.J. The Measurement of Place Attachment: Validity and Generalizability of a Psychometric Approach. In 2003; Vol. 49, pp. 830-840.
9. Buttazzoni, A.; Doherty, S.; Minaker, L. How Do Urban Environments Affect Young People's Mental Health?A Novel Conceptual Framework to Bridge Public Health, Planning and Neurourbanism. Public Health Rep 2021, 137, 48-61, https://doi.org/10.1177/0033354920982088.
10. Gifford, R. Environmental Psychology Matters. Annu Rev Psychol 2014, 65, 541-579, https://doi.org/10.1146/annurev-psych-010213-115048.
11. Putnam, R.D. Bowling alone: The collapse and revival of American community., Touchstone Books/Simon & Schuster: New York, NY, US, 2000; p. 541, ISBN 0-7432-0304-6 (Paperback).
12. Pretty, J.; Peacock, J.; Hine, R.; Sellens, M.; South, N.; Griffin, M. Green exercise in the UK countryside: Effects on health and psychological well-being, and implications for policy and planning. J Environ Plann Man 2007, 50, 211-231, https://doi.org/10.1080/09640560601156466.
13. Kahneman, D.; Deaton, A. High income improves evaluation of life but not emotional well-being. P Natl Acad Sci Usa 2010, 107, 16489-16493, 10.1073/pnas.1011492107.
14. Vidal Rua, S. Perceptions of tourism: a study of residents' attitudes towards tourism in the city of Girona. Journal of Tourism Analysis: Revista De Análisis Turístico 2020, 27, 165-184, https://doi.org/10.1108/JTA-03-2019-0015.
15. Ma, C.; Song, W.; Xu, C. Factors Influencing Resident Satisfaction with Afforestation in the Plains: Beijing as a Case Study. Sustainability-Basel 2023, 15, 6856, https://doi.org/10.3390/su15086856.
16. Majumdar, J.; Mal, A.; Gupta, S. Heuristic Model to Improve Feature Selection Based on Machine Learning in Data Mining, In Proceedings of the 2016 6th International Conference on Confluence The Next Generation Information Technology Summit (Confluence), Noida, India, 14-15 January 2016; pp. 73-77.
17. Yang, X.Y.; Liu, J.; Zhang, M.Q.; Niu, K.; VanAlbada, G.D. A new multi-class SVM algorithm based on one-class SVM, In Proceedings of the Computational Science (ICCS 2007), Beijing, China, 27-30 May 2007; p. 677.
18. Barreira, A.P.; Agapito, D.; Panagopoulos, T.; Guimaraes, M.H. Exploring residential satisfaction in shrinking cities: a decision-tree approach. Urban Res Pract 2017, 10, 156-177, https://doi.org/10.1080/17535069.2016.1179784.
19. Le, L.T.; Nguyen, H.; Dou, J.; Zhou, J. A Comparative Study of PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN in Estimating the Heating Load of Buildings' Energy Efficiency for Smart City Planning. Appl Sci-Basel 2019, 9, 2630, https://doi.org/10.3390/app9132630.
20. Dai, H.B.; Huang, G.Q.; Zeng, H.B.; Yu, R.C. Haze Risk Assessment Based on Improved PCA-MEE and ISPO-LightGBM Model. Systems-Basel 2022, 10, 263, https://doi.org/10.3390/systems10060263.
21. Deb, S.; Gao, X.Z. Prediction of Charging Demand of Electric City Buses of Helsinki, Finland by Random Forest. Energies 2022, 15, 3679, https://doi.org/10.3390/en15103679.
22. Abraham, R.; Samad, M.E.; Bakhach, A.M.; El-Chaarani, H.; Sardouk, A.; Nemar, S.E.; Jaber, D. Forecasting a Stock Trend Using Genetic Algorithm and Random Forest. J Risk Financ Manag 2022, 15, 188, https://doi.org/10.3390/jrfm15050188.
23. Badawy, M.; Ramadan, N.; Hefny, H.A. Healthcare predictive analytics using machine learning and deep learning techniques: a survey. Journal of Electrical Systems and Information Technology 2023, 10, 40, http://doi.org/10.1186/s43067-023-00108-y.
24. Chen, L.; Han, B.; Wang, X.; Zhao, J.; Yang, W.; Yang, Z. Machine Learning Methods in Weather and Climate Applications: A Survey. Applied Sciences 2023, 13, 12019, https://doi.org/10.3390/app132112019.
25. Boston, T.; Van Dijk, A.; Larraondo, P.R.; Thackway, R. Comparing CNNs and Random Forests for Landsat Image Segmentation Trained on a Large Proxy Land Cover Dataset. Remote Sens-Basel 2022, 14, 3396, https://doi.org/10.3390/rs14143396.
26. Li, W.Q.; Shi, H.W.; IEEE. A Method Used for Evaluating Bids Based on FCE-AHM, In Proceedings of the 2009 International Conference on Information Management, Innovation Management and Industrial Engineering, Xi'an, China, 31 December 2009; p. 499.

27. Loecher, M. Unbiased variable importance for random forests. Commun Stat-Theor M 2022, 51, 1413-1425, https://doi.org/10.1080/03610926.2020.1764042.
28. Niu, Q.F.; Wang, G.; Liu, B.; Zhang, R.Z.; Lei, J.J.; Wang, H.; Liu, M.Z. Selection and prediction of metro station sites based on spatial data and random forest: a study of Lanzhou, China. Sci Rep-Uk 2023, 13, 22542, https://doi.org/10.1038/s41598-023-49877-6.
29. Chen, W.; Tian, Y.; Wang, Y.; Yan, H.; Wang, Y. Cause Identification and Coupling Relationship Analysis of Urban Problems: A Case Study of Poor Parking Convenience. Buildings-Basel 2024, 14, 516, https://doi.org/10.3390/buildings14020516
30. Lu, X.; Xiao, Y.; Li, M. The Eco-Sustainable Planning and Revitalisation of Historic and Cultural Blocks: A Case Study of Jiang'an South District Renovation in Wuhan. In 2022; Vol. 08, pp. 51-56.
31. Xiang, X.; Huang, Y. Smart City Promotes Urban Sustainable Development. China Quality and Standards Review 2019, 01, 32-35.
32. Easterlin, R.A.; Morgan, R.; Switek, M.; Wang, F. China's life satisfaction,1990–2010. Proceedings of the National Academy of Sciences 2012, 109, 9775-9780, https://doi.org/10.1073/pnas.1205672109.
33. Li, X.M.; Liu, H. The Influence of Subjective and Objective Characteristics of Urban Human Settlements on Residents' Life Satisfaction in China. Land-Basel 2021, 10, 1400, https://doi.org/10.3390/land10121400.
34. Dempsey, N.; Bramley, G.; Power, S.; Brown, C. The social dimension of sustainable development: Defining urban social sustainability. Sustain Dev 2011, 19, 289-300, https://doi.org/10.1002/sd.417.
35. Xu, J.; Zhang, W.; Chen, L. Impact of urban population density on perception of human settlements in Hangzhou. Scientia Geographica Sinica 2022, 42, 208-218, https://doi.org/10.13249/j.cnki.sgs.2022.02.003.
36. Dzhambov, A.M.; Dimitrova, V.; Germanova, N.; Burov, A.; Brezov, D.; Hlebarov, I.; Dimitrova, R. Joint associations and pathways from greenspace, traffic-related air pollution, and noise to poor self-rated general health: A population-based study in Sofia, Bulgaria. In 2023; Vol. 231, p. 116087.
37. Khaled Al Shawabkeh, R.; Alobaidat, E.; Ibraheem Alhaddad, M.; Alzouby, A.M. The role of social infrastructure services in developing the city centre planning: A framework for delivering sustainable cities in Jordan. Ain Shams Eng J 2022, 13, 101800, https://doi.org/10.1016/j.asej.2022.101800.
38. Newell, R.; Picketts, I. Spaces, places and possibilities: A participatory approach for developing and using integrated models for community planning. In 2020; Vol. 6, p. 100040.
39. Seo, S.; Shanklin, C.W. Effect of Dining Frequency on Behavioral Intentions Related to Dining Services in Continuing Care Retirement Communities. Journal of the American Dietetic Association 2005, 105, 47, https://doi.org/10.1016/j.jada.2005.05.156.
40. Yu, P.; Yung, E.H.K.; Chan, E.H.W.; Wang, S.; Chen, Y.; Chen, Y. Capturing open space fragmentation in high–density cities: Towards sustainable open space planning. In 2023; Vol. 154, p. 102927.
41. Brauman, K.A.; Daily, G.C.; Duarte, T.K.E.; Mooney, H.A. The Nature and Value of Ecosystem Services: An Overview Highlighting Hydrologic Services. Annu Rev Env Resour 2007, 32, 67-98, https://doi.org/10.1146/annurev.energy.32.031306.102758.
42. Lu, Z.; Guan, Y.; Shao, C.; Niu, R. Assessing the health impacts of PM2.5 and ozone pollution and their comprehensive correlation in Chinese cities based on extended correlation coefficient. In 2023; Vol. 262, p. 115125.
43. Drew, J.; Dollery, B.; Kortt, M.A. Can't Get No Satisfaction? The Association Between Community Satisfaction and Population Size for Victoria. Aust J Publ Admin 2016, 75, 65-77, https://doi.org/10.1111/1467-8500.12117.
44. Chen, L.; Mak, C.M. Integrated impacts of building height and upstream building on pedestrian comfort around ideal lift-up buildings in a weak wind environment. In 2021; Vol. 200, p. 107963.
45. Ho, L.; Barthel, M.; Panique-Casso, D.; Vermeulen, K.; Bruneel, S.; Liu, X.; Bodé, S.; Six, J.; Boeckx, P.; Goethals, P. Impact of salinity gradient, water pollution and land use types on greenhouse gas emissions from an urbanized estuary. In 2023; Vol. 336, p. 122500.
46. Cosic, A.; Stadler, M.; Mansoor, M.; Zellinger, M. Mixed-integer linear programming based optimization strategies for renewable energy communities. In 2021; Vol. 237, p. 121559.
47. O'Donnell, J.; Cárdenas, D.; Orazani, N.; Evans, A.; Reynolds, K.J. The longitudinal effect of COVID-19 infections and lockdown on mental health and the protective effect of neighbourhood social relations. In 2022; Vol. 297, p. 114821.

48. Luo, X.; Ren, M.; Zhao, J.; Wang, Z.; Ge, J.; Gao, W. Life cycle assessment for carbon emission impact analysis for the renovation of old residential areas. In 2022; Vol. 367, p. 132930.
49. Caixeta Szymanski Nogueira, A.C.; D Diaz, C.E. Evaluating public transport accessibility and walkability in Pasig City (Philippines) and their correlation to socioeconomic factors at the Barangay level. In 2023; Vol. 9, p. 100117.
50. Serbanica, C.; Constantin, D.L. Misfortunes never come singly. A holistic approach to urban resilience and sustainability challenges. In 2023; Vol. 134, p. 104177.
51. Aigwi, I.E.; Filippova, O.; Sullivan-Taylor, B. Public perception of heritage buildings in the city-centre of Invercargill, New Zealand. In 2023; Vol. 34, p. 100538.
52. Renne, J.L.; Listokin, D. Transit-oriented development and historic preservation across the United States: A geospatial analysis. In 2021; Vol. 10, p. 100373.
53. Feng, W.; Liu, Y.; Li, D. Emotional or rational? The congruence effect of message appeals and country stereotype on tourists' international travel intentions. In 2022; Vol. 95, p. 103423.
54. O Toole, C.; Martinez-Cillero, M.; Ahrens, A. Price regulation, inflation, and nominal rigidity in housing rents. In 2021; Vol. 52, p. 101769.
55. Kang, S.; Son, H.; Song, B.K. The effect of housing price inequality on mental health. In 2023; Vol. 85, p. 102460.
56. Sarker, M.S.H. Assessing levels of migrant-friendliness in the context of vulnerability to climate variability, change and environmental hazard: A comparison of two different-sized cities. In 2022; Vol. 68, p. 102525.
57. Li, J.; Sun, S.; Li, J. The dawn of vulnerable groups: The inclusive reconstruction mode and strategies for urban villages in China. In 2021; Vol. 110, p. 102347.
58. Golan, J.; Sicular, T.; Umapathi, N. Unconditional Cash Transfers in China: Who Benefits from the Rural Minimum Living Standard Guarantee (Dibao) Program? In 2017; Vol. 93, pp. 316-336.
59. Koetter, T.; Sikder, S.K.; Weiss, D. The cooperative urban land development model in Germany - An effective instrument to support affordable housing. In 2021; Vol. 107, p. 105481.
60. Ma, Y.; Gu, X.; Zhang, W.; Hu, S.; Liu, H.; Zhao, J.; Chen, S. Evaluating the effectiveness of crosswalk tactile paving on street-crossing behavior: A field trial study for people with visual impairment. In 2021; Vol. 163, p. 106420.
61. Huang, L.; Zhao, X.; Li, Y.; Ma, J.; Yang, L.; Rong, J.; Wang, Y. Optimal design alternatives of advance guide signs of closely spaced exit ramps on urban expressways. In 2020; Vol. 138, p. 105465.
62. Gong, Y.; Li, Y.; Sun, Y. Waste sorting behaviors promote subjective well-being: A perspective of the self-nature association. In 2023; Vol. 157, pp. 249-255.
63. Bin Omar, M.; Ali, H.B.; Bin Sipan, I.A.; Bin Abdullah, S.; Sapri, M.B.; Bin Daud, D.; Achu, K. Identification of Key Drivers of Property Management Capability Index for Stratified Residential Property Management in Malaysia, In Proceedings of the 29th International-Business-Information-Management-Association Conference (IBIMA), Vienna, Austria, 3-4 May 2017; pp. 3775-3787.
64. López, I.; Gutiérrez, V.; Collantes, F.; Gil, D.; Revilla, R.; Luis Gil, J. Developing an indicators plan and software for evaluating Street Cleanliness and Waste Collection Services. J Urban Manag 2017, 6, 66-79, https://doi.org/10.1016/j.jum.2017.06.002.
65. Falk, C. Rehabilitation of manhole covers. In 1999; Vol. 14, pp. 39-46.
66. Yamaguchi, T.; Mizutani, T. Detection and localization of manhole and joint covers in radar images by support vector machine and Hough transform. In 2021; Vol. 126.
67. Rodríguez-Cuenca, B.; García-Cortés, S.; Ordóñez, C.; Alonso, M.C. Automatic Detection and Classification of Pole-Like Objects in Urban Point Cloud Data Using an Anomaly Detection Algorithm. Remote Sens-Basel 2015, 7, 12680-12703, https://doi.org/10.3390/rs71012680.
68. Hong, S.I.; Ryu, H.S.; Yoon, D.H.; In, C.G.; Park, J.C.; Lin, C.H. A Development of LED-IT-Sensor Integration Streetlight Management System on Ad-hoc, In Proceedings of the 2011 IEEE Region 10 Conference (TENCON 2011), Bali, Indonesia, 21-24 Nov 2011; pp. 1331-1335.
69. Macea, L.F.; Serrano, I.; Carcache-Guas, C. A reservation-based parking behavioral model for parking demand management in urban areas. In 2023; Vol. 86, p. 101477.
70. Cleland, C.L.; Williams, A.J.; Kee, F.; Jepson, R.; Kelly, M.P.; Milton, K.; Nightingale, G.; Cope, A.; Hunter, R.F. Can 20mph speed limit interventions influence liveability? A natural experiment using the Microscale Audit of Pedestrian Streetscapes Liveability (MAPS-Liveability) and Google Street View. In 2024; Vol. 35, p. 101779.

71. Chu-Ketterer, L.J.; Platten, W.E.; Bolenbaugh, S.; Haxton, T. Resilience Analysis and Emergency Response Evaluation for Drinking Water Systems. J Awwa 2023, 115, 32-42, https://doi.org/10.1002/awwa.2107.
72. Miles, S.B.; Gallagher, H.; Huxford, C.J. Restoration and Impacts from the September 8, 2011, San Diego Power Outage. J Infrastruct Syst 2014, 20, 5014002, https://doi.org/10.1061/(ASCE)IS.1943-555X.0000176.
73. Bostjancic, E.; Slana, Z. The Role of Talent Management Comparing Medium-Sized and Large Companies - Major Challenges in Attracting and Retaining Talented Employees. In 2018; Vol. 9, p. 1750.
74. Widerszal-Bazyl, M.; Radkiewicz, P.; Hasselhorn, H.M.; Conway, P.M.; Heijden, B.I.J.M. The Demand-Control-Support model and intent to leave across six European countries: The role of employment opportunities. Work Stress 2008, 22, 166-184, https://doi.org/10.1080/02678370801999750.
75. Corrado, G.; Corrado, L. Inclusive finance for inclusive growth and development. In 2017; Vol. 24, pp. 19-23.
76. Tian, Y.; Zhang, Y.; Zhang, T.; Zhu, Y. Co-agglomeration, technological innovation and haze pollution: An empirical research based on the middle reaches of the Yangtze River urban agglomeration. In 2024; Vol. 158, p. 111492.
77. Liao, B.; Li, L. Spatial division of labor, specialization of green technology innovation process and urban coordinated green development: Evidence from China. In 2022; Vol. 80, p. 103778.
78. Wittmer, J. Dirty work in the clean city: An embodied Urban Political Ecology of women informal recyclers' work in the 'clean city'. Environ Plan E-Nat 2023, 6, 1343-1365, https://doi.org/10.1177/25148486221102374.
79. Zhang, B.S.; Qi, R.K. Transportation Infrastructure, Innovation Capability, And Urban Economic Development. Transform Bus Econ 2021, 20, 526-545.
80. Tiitu, M.; Nyberg, E.; Halonen, J.I.; Pasanen, T.P.; Viinikka, A.; Lehtimäki, J.; Lanki, T.; Vierikko, K. Comparing city practitioners and residents perceptions of a liveable neighbourhood in Finland. In 2023; Vol. 32, pp. 1118-1145.
81. De Lotto, R. Management of urban smart systems. Smart Struct Syst 2022, 30, 333-338, https://doi.org/10.12989/sss.2022.30.3.333.
82. Phonapichat, P.; Wongwanich, S.; Sujiva, S. The Development of Diagnostic Test Using the Attribute Hierarchy Method. In 2016; Vol. 217, pp. 594-597.
83. Zhong, J.; Li, Z.; Zhang, D.; Yang, J.; Zhu, J. An evaluation framework for urban ecological compensation priority in China based on meta-analysis and fuzzy comprehensive evaluation. In 2024; Vol. 158, p. 111284.
84. Hemalatha, S.; Dumpala, L.; Balakrishna, B. Service quality evaluation and ranking of container terminal operators through hybrid multi-criteria decision making methods. The Asian Journal of Shipping and Logistics 2018, 34, 137-144, https://doi.org/10.1016/j.ajsl.2018.06.010.
85. Boulesteix, A.L.; Bender, A.; Bermejo, J.L.; Strobl, C. Random forest Gini importance favours SNPs with large minor allele frequency: impact, sources and recommendations. Brief Bioinform 2012, 13, 292-304, https://doi.org/10.1093/bib/bbr053.
86. Khan, Z.; Gul, N.; Faiz, N.; Gul, A.; Adler, W.; Lausen, B. Optimal Trees Selection for Classification via Out-of-Bag Assessment and Sub-Bagging. In 2021; Vol. 9, pp. 28591-28607.
87. Bylander, T. Estimating generalization error on two-class datasets using out-of-bag estimates. Mach Learn 2002, 48, 287-297, https://doi.org/10.1023/A:1013964023376.
88. Karunasingha, D.S.K. Root mean square error or mean absolute error? Use their ratio as well. In 2022; Vol. 585, pp. 609-629.
89. Emmert-Streib, F.; Dehmer, M. Evaluation of Regression Models: Model Assessment, Model Selection and Generalization Error. Mach Learn Know Extr 2019, 1, 521-551, https://doi.org/10.3390/make1010032.
90. Xie, Y.; Qi, C.; Gu, Y. The analysis of the coupling relation and timing characteristics between the new-type urbanization andurban agricultural development:A case study of Wuhan city. Chinese Journal of Agricultural Resources and Regional Planning 2021, 42, 215-224.
91. Cui, H.; Fang, H.; Tian, Y.; Zheng, W.; Li, W.; Tian, W. Evaluation of Livability of Wuhan under Ecological Construction and Analysis of Its Spatial Pattern. Sustainability-Basel 2022, 14, 11283, https://doi.org/10.3390/su141811283
92. Sheng, S.; Song, W.; Lian, H.; Ning, L. Review of Urban Land Management Based on Bibliometrics. Land-Basel 2022, 11, 1968, https://doi.org/10.3390/land11111968.
93. Liu, S.; Tan, S. Building a New Framework for Urban Parking Facilities Research with Quality Improvement: The Case of Chongqing, China. Int J Env Res Pub He 2023, 20, 607, https://doi.org/10.3390/ijerph20010607.
94. Erik De Lima Andrade, D.C.D.C. Environmental noise in hospitals: a systematic review. Environmental Science and Pollution Research International 2021, 16, 19629-19642, https://doi.org/10.1007/s11356-021-13211-2.

95. Yuan, M.; Yin, C.; Sun, Y.; Chen, W. Examining the associations between urban built environment and noise pollution in high-density high-rise urban areas: A case study in Wuhan, China. Sustain Cities Soc 2019, 50, 101678, https://doi.org/10.1016/j.scs.2019.101678.
96. El-Fadel, M.; Sbayti, H. Parking Facilities in Urban Areas: Air and Noise Impacts. J Urban Plan Dev 2001, 127, 16-33, https://doi.org/10.1061/（ASCE）0733-9488（2001）127：1（16）.
97. Nikoofam, M.; Mobaraki, A.; Taylor, G. Assessment of Quality of Life in the Urban Environment; Case Study: Famagusta, N. Cyprus. In 2020; Vol. 8, pp. 860-872.
98. Zhao, L.; Li, H.; Sun, Y.; Huang, R.; Hu, Q.; Wang, J.; Gao, F. Planning Emergency Shelters for Urban Disaster Resilience: An Integrated Location-Allocation Modeling Approach. Sustainability-Basel 2017, 9, 2098, https://doi.org/10.3390/su9112098.
99. Wang, H.; Gui, H.; Ren, C.; Liu, G. Factors Influencing Urban Residents' Intention of Garbage Sorting in China: An Extended TPB by Integrating Expectancy Theory and Norm Activation Model. Sustainability-Basel 2021, 13, 12985, https://doi.org/10.3390/su132312985.
100. NamGung, H.; Kim, C.; Choe, K.; Ri, C.; Kim, Y.; Ri, M. Research Progress of Road Intersection Design Analysis. In 2020; Vol. 7, pp. 245-256.
101. Liu, J.; Ong, H.Y. Can Malaysia's National Affordable Housing Policy Guarantee Housing Affordability of Low-Income Households? Sustainability-Basel 2021, 13, 8841, https://doi.org/10.3390/su13168841.
102. Saidu, A.I.; Yeom, C. Success Criteria Evaluation for a Sustainable and Affordable Housing Model: A Case for Improving Household Welfare in Nigeria Cities. Sustainability-Basel 2020, 12, 656, https://doi.org/10.3390/su12020656.
103. Wang, Q.; Teo, T. Explaining the relationships among components of intercultural competence: A structural equation modelling approach. In 2024; Vol. 99, p. 101953.
104. Pluchinotta, I.; Zhou, K.; Moore, G.; Salvia, G.; Belesova, K.; Mohajeri, N.; Hale, J.; Davies, M.; Zimmermann, N. Co-producing knowledge on the use of urban natural space: Participatory system dynamics modelling to understand a complex urban system. In 2024; Vol. 353, p. 120110.
105. Lee, S. Measuring the influence of transit accessibility on housing and transportation expenditures in the U.S.: A propensity score matching approach. In 2023; Vol. 14, p. 101092.