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Article

Evaluating Key Spatial Indicators for Shared Autonomous Vehicle Integration in Old Town Spaces

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Abstract

As Shared Autonomous Vehicles (SAVs) emerge as a transformative force in urban mobility, integrating them into dense, historic urban environments presents distinct spatial and planning challenges—such as narrow street patterns, irregular road networks, and the need to protect cultural heritage. This study investigates the spatial adaptability of SAVs in Suzhou old town, a representative example of East Asian heritage cities. To assess spatial readiness, a hybrid weighting approach combining the Analytic Hierarchy Process (AHP) and the Entropy Weight Method (EWM) is used to evaluate 22 spatial indicators across livability, mobility, and spatial quality. These weighted indicators are mapped using a spatial density analysis based on Point of Interest (POI) data, revealing urban service distribution patterns and spatial mismatches. Results show that "Accessibility to Transportation Hubs" receives the highest composite weight, emphasizing the priority of linking SAVs with existing subway and bus networks. Environmental comfort factors—such as air quality, noise reduction, and access to green and recreational spaces—also rank highly, reflecting a growing emphasis on urban livability. Drawing on these findings, this study proposes four strategic directions for SAV integration that focus on network flexibility, public service redistribution, ecological enhancement, and cultural preservation. The proposed framework provides a transferable planning reference for historic urban areas transitioning toward intelligent, human-centered mobility systems.

Keywords: Shared Autonomous Vehicles (SAVs); old town regeneration; ArcGIS GeoPlanner; quantitative research; AHP–EWM

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1. Introduction

Historic urban cores, particularly in East Asian cities, are increasingly facing the dual pressures of modern mobility demands and cultural heritage preservation. As Shared Autonomous Vehicles (SAVs) emerge as a transformative force in urban mobility, their potential integration into dense, irregular, and historically significant urban fabrics poses both opportunities and challenges. This study investigates these dynamics in Suzhou old town, an emblematic case of an East Asian heritage city undergoing transition toward intelligent mobility (Figure 1).

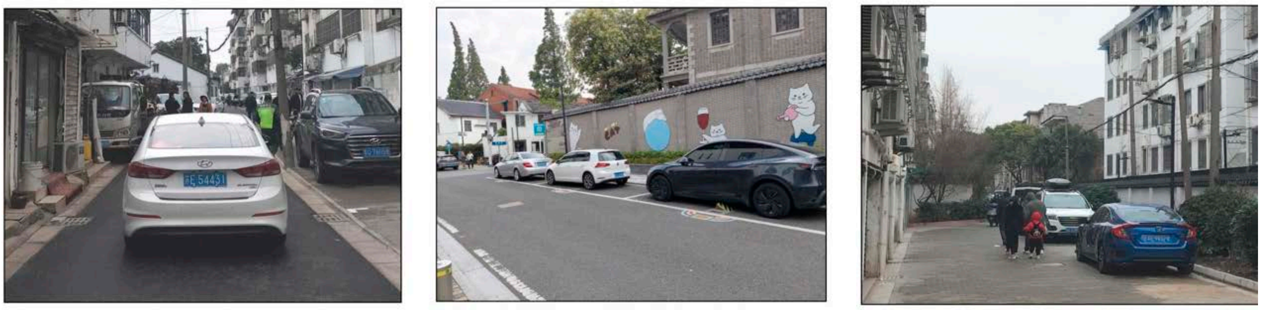

Figure 1. The current traffic situation in Suzhou old town (the streets and alleys are relatively narrow and there is a shortage of parking Spaces).

Recent decades have seen the rapid expansion of urban populations globally, driven by increased mobility and economic globalization [1]. In China, the urbanization rate surpassed 60% by 2019, with rapid growth placing intensified pressures on land use and urban infrastructure [2,3]. Old towns, typically established in earlier phases of urban development, are now constrained by their legacy street networks and aging facilities [4], resulting in heightened tensions between preservation and modernization. In Suzhou, an emerging first-tier city, this challenge is particularly acute [5]. Moreover, urbanization exacerbates environmental issues: the National Climate Center of China reports a record number of extreme heat days in recent years [6], a trend consistent with broader global climate shifts [7].

Traditional transport planning, often centered on high-speed infrastructure, has failed to adequately resolve problems like congestion and emissions. Transportation accounts for approximately one-quarter of greenhouse gas emissions in the European Union [8], and vehicle emissions tend to increase with reduced traffic speeds, particularly under congested conditions [9]. These limitations point to the urgent need for low-carbon, flexible, and space-efficient mobility systems.

SAVs as a hybrid of public and on-demand services, are gaining traction worldwide. They offer a promising strategy to address the urban challenges of congestion, emissions, and inefficient land use [10–12]. A single SAVs has the potential to replace multiple private vehicles [13], thereby reducing space dedicated to parking and roadways. Among various smart mobility services, ride-hailing platforms have exhibited particularly rapid growth, supporting the scalability of SAVs-based systems [11].

In the context of aging urban cores, SAVs may serve as a tool for regenerating underperforming infrastructure and enhancing urban livability. In China, where urban development has shifted from expansion to renewal [14], understanding how SAVs interact with traditional urban form is a pressing research need [15]. SAVs could reshape spatial morphology through changes in residential patterns, parking allocation, regional accessibility, and street-level design [16–18]. For instance, a study in Rome found that central city residents are more willing than suburban residents to relocate outward in the SAVs era [19]. Meanwhile, Suzhou has made parking reform a top municipal priority since 2018 [20]. Modeling studies suggest that SAVs can significantly reduce parking demand: in a grid city simulation, 1 SAV could replace 12 private vehicles and eliminate up to 11 parking spaces [21]; in Singapore, over 85% of parking could become obsolete with full SAVs adoption [22]. These spatial savings may be amplified by the compact design of SAV-related facilities, which exclude pedestrian-centric elements like signage and elevators.

SAVs also promise to enhance accessibility and reduce transportation costs [23], but this raises concerns about equitable service provision. At the street level, SAVs are expected to impact the design of roadways, including the need for efficient and safe pick-up/drop-off

(PUDO) zones, which could either support or disrupt non-motorized transport systems [22]. If not carefully planned, SAVs infrastructure might fragment pedestrian and cycling networks. Nevertheless, the reduction in space allocated to private cars opens new possibilities: wider sidewalks, more bike lanes, and reimagined public spaces can contribute to a more livable, human-scale environment.

In the integrated study of urban regeneration and smart mobility deployment, Geographic Information System technologies provide essential support for the analysis of multidimensional spatial data. ArcGIS GeoPlanner, as a visual decision-making platform tailored for urban planning and scenario evaluation, is widely used in complex tasks such as land use analysis, transportation accessibility assessment, and environmental impact evaluation. Its model-driven approach and layer overlay capabilities enable researchers to rapidly identify urban development bottlenecks based on spatial element relationships and to quantify the potential impacts of SAVs deployment on urban spatial structure, thereby enhancing the scientific validity and practical feasibility of planning recommendations [24].

Although this study focuses on Suzhou old town as a representative historical district in China, historic cities around the world (such as Rome, Istanbul, Kyoto, and Prague) face similar challenges in balancing the development of smart mobility infrastructure, including SAVs, with the preservation of cultural heritage authenticity and integrity.

The introduction of SAVs could lead to a reduction in space allocated to private motor vehicles, creating new opportunities to expand sidewalks and bicycle lanes, enhance wayfinding for non-motorized modes, and increase the availability of public street space. These changes could significantly enhance the attractiveness and effectiveness of active transportation systems in old towns.

This study emphasizes the integration of expert evaluations with the current physical conditions of Suzhou old town to examine the potential spatial impacts of SAVs. By identifying the relative weights and priority levels of SAVs induced spatial transformations, the research seeks to clarify key concerns and strategic directions for urban regeneration within this historically and structurally unique urban context.

Significance of This Study:

1. From an expert perspective, this study explores the potential spatial impacts of SAVs technologies on old town areas, offering strategic insights for facilitating the mutual adaptation and integrated transition between SAVs systems and traditional urban environments. These insights contribute to the formulation of more effective and context sensitive urban regeneration strategies.
2. The findings aim to support evidence-based decision making by governments and urban planning departments, offering user-centered perspectives to guide policy development and promote a more sustainable transformation of old town urban spaces.

Objectives of This Study:

1. To investigate the potential spatial impacts of SAVs and identify key areas of concern, based on both subjective and objective expert evaluations.
2. To propose context specific planning strategies by integrating expert insights with spatial analysis of the current built environment in Suzhou old town using the ArcGIS GeoPlanner platform. These strategies are intended to inform future policy formulation and spatial governance practices.

2. Materials and Methods

2.1. Study Area

This research centers on Suzhou old town as the primary case study, focusing on its unique urban spatial structure. Covering approximately 14.2 km^2 and home to around

252,000 residents based on 2020 subdistrict level statistics, the area is predominantly composed of residential zones, public administration and service facilities, and commercial land uses [25]. The street network reflects Suzhou's historical evolution, with a distinctive layout organized around its ancient water systems, forming a dual grid structure that integrates both roads and canals [26].

Two key reasons support the selection of Suzhou old town for this study:

Advanced Urbanization and Pilot Status: Suzhou has undergone rapid urban transformation, with its urbanization rate increasing from 70.07% (Sixth National Census) to 81.72%. During the same timeframe, the permanent population grew from 10.45 million to 12.74 million, and the urban population rose from 7.32 million to 10.41 million [27]. As a pilot city for national urban-rural integration, Suzhou exemplifies both mature urban development and evolving spatial governance in high-density regions. Its strategic positioning within East Asia also reflects broader trends in integrated urban–rural planning and modernization [28].

Cultural Heritage and Spatial Continuity: The physical form and spatial organization of Suzhou old town have remained largely consistent for over two millennia [26]. The preservation of traditional building facades, historic urban patterns, and local cultural practices contributes to a rich foundation for heritage led regeneration [28]. As such, exploring the integration of SAVs within this context not only responds to local planning needs but also offers transferable insights for historic urban areas in East Asia and beyond (Figure 2).

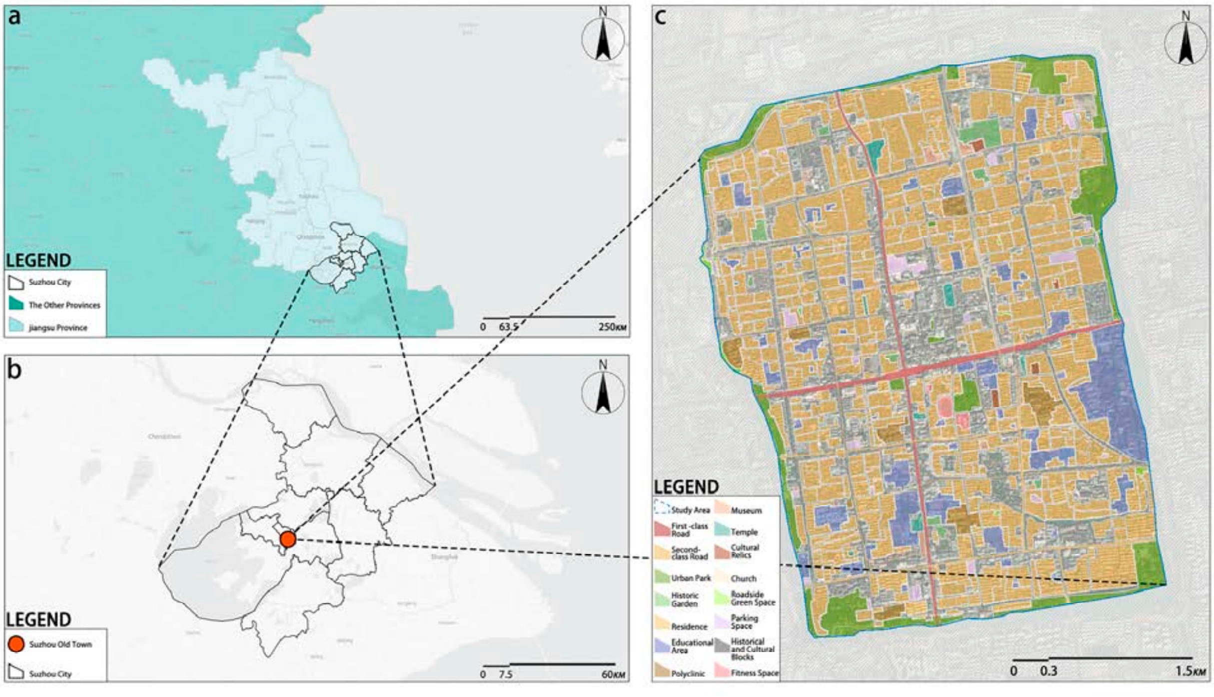

Figure 2. Location map of Suzhou old town (**a**) Jiangsu Province, China, (**b**) map of Suzhou, and (**c**) map of Suzhou old town and functional zone.

Representative Challenges of Historic Urban Cores: Suzhou old town embodies typical challenges faced by global heritage cities, such as narrow streets, aging infrastructure, spatial congestion, and the need to balance modern mobility with preservation mandates. This makes it an ideal laboratory to assess the adaptability and planning potential of SAVs in complex, historically constrained environments.

Data Accessibility and Spatial Richness: The availability of detailed POI datasets, high-resolution population statistics, and built environment data at the subdistrict level enables robust geospatial analysis. This ensures reproducibility of this study and supports evidence-based scenario planning for SAVs deployment.

2.2. Study Scope

This study focuses on L4–L5 level small 4–5 seater SAVs with enterprises as the operating entities. The vehicle models are mainly compact autonomous driving taxis (Robo-taxis), similar to the vehicle models used on the Apollo [29] or Waymo RoboTaxi platform [30].

2.3. Questionnaire Design

The purpose of this questionnaire is to investigate expert perspectives and weight evaluations regarding the integration of SAVs into old town urban spaces. The three-tier evaluation framework used in the questionnaire was developed based on the findings from our team's prior quantitative research [31] (Table 1).

Table 1. The three-tier evaluation framework.

Objective (A)	Criterion Layer (B)	Index Layer (C)	Source
A1 The Living Environment, Travel Experience and Spatial Quality Demands of the Residents in Old Town	B1 Influencing Factors of Residential Area Selection	C1 Residential Convenience of Travel C2 Residential Prices C3 Residential Environment C4 Accessibility of Residential Areas	[31]
	B2 The Daily Functional Space Requirements of Old Town	C5 Availability of Parking Space C6 Urban Fitness Spaces C7 Park and Green Spaces	
	B3 Perception of Environmental Quality of Traffic Space in Old Town	C8 Aesthetic and Personalized Design of Transportation Facilities C9 Number of Traffic Barriers and Traffic Lights in Old Town C10 Density of PUDO Points in Old Town C11 Density of Public Transport Stops in Old Town C12 Barrier-Free Transportation Facilities in Old Town C13 Density of Gasoline and Charging Stations C14 Air Quality and Noise	
	B4 Dimension of SAVs Service Quality Sense	C15 Travel Cost C16 Travel Safety (Including vehicle driving safety, the safety of women using vehicles at night, and the risk of scratches on SAVs) C17 Social Needs During Travel (Non-carpooling SAVs services can reduce contact with strangers, including unfamiliar passengers and drivers, and are more friendly to taxi hailing users who have a fear of strangers) C18 Travel Efficiency (Including being able to hail a vehicle quickly and not refusing to pick up passengers in remote areas)	
	B5 The Accessibility Requirements of Multi-functional Urban Spaces	C19 Accessibility to Suburban Scenic Spots C20 Accessibility to Transportation Hubs C21 Accessibility to Cultural and Sports Spaces for Residents C22 Comprehensive Accessibility in Old Town	

This study designed two sets of expert questionnaires. Expert Questionnaire 1 consists of two sections: the first section collects demographic information of the participating experts, including gender, age group, and current professional specialization. The second section asks experts to perform pairwise comparisons of criterion layers and sub-indicators.

Since the data analysis of this questionnaire employs the subjective Analytical Hierarchy Process (AHP), Expert Questionnaire 1 was developed based on the AHP hierarchical structure model (see Figure 3) to guide the evaluation of the relative importance of indicators. The scoring method utilizes the standard nine-point scale for pairwise comparisons (see Table 2).

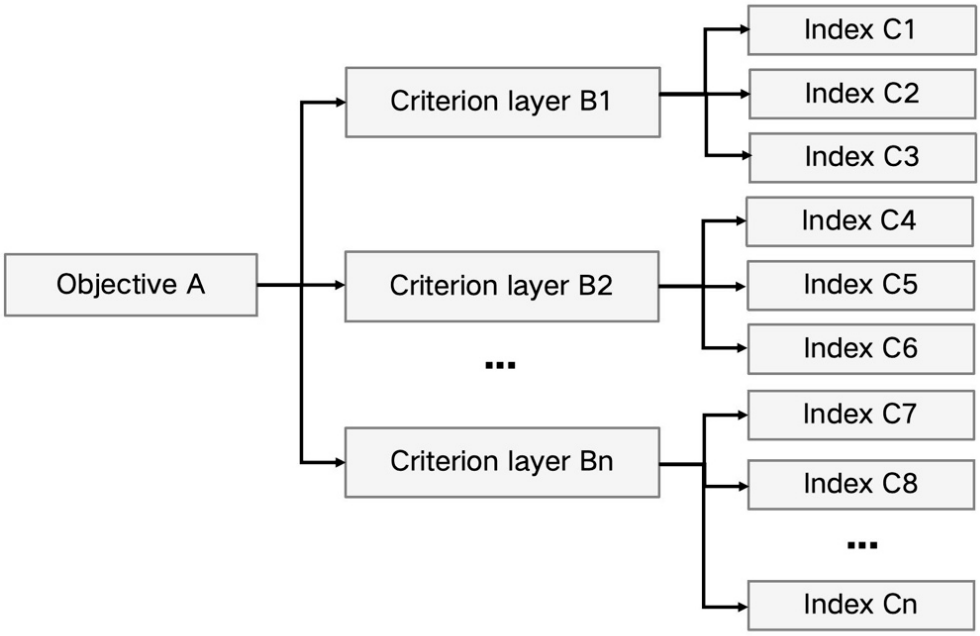

Figure 3. The AHP Structural Hierarchy model.

Table 2. Ninth-point scale for AHP.

Scale Value	Meaning
1	Indicates that the two factors are equally important.
3	Indicates that the former factor is slightly more important than the latter.
5	Indicates that the former factor is moderately more important than the latter.
7	Indicates that the former factor is strongly more important than the latter.
9	Indicates that the former factor is extremely more important than the latter.
2/4/6/8	Represent intermediate values between the above levels of judgment.

Expert Questionnaire 2 also consists of two sections. The first section collects demographic information of the participating experts, including gender, age group, and current professional specialization. The second section requires experts to rate the importance of the index level indicators using a Likert scale. The importance levels are categorized into five degrees: "very unimportant," "unimportant," "moderately important," "important," and "very important," assigned values from 1 to 5 respectively (Table 3).

Table 3. Likert scale for EWM.

Scale Value	Meaning
1	Very unimportant
2	Unimportant
3	Moderately important
4	Important
5	Very important

2.4. Data Analysis

The data analysis steps are shown in the Figure 4.

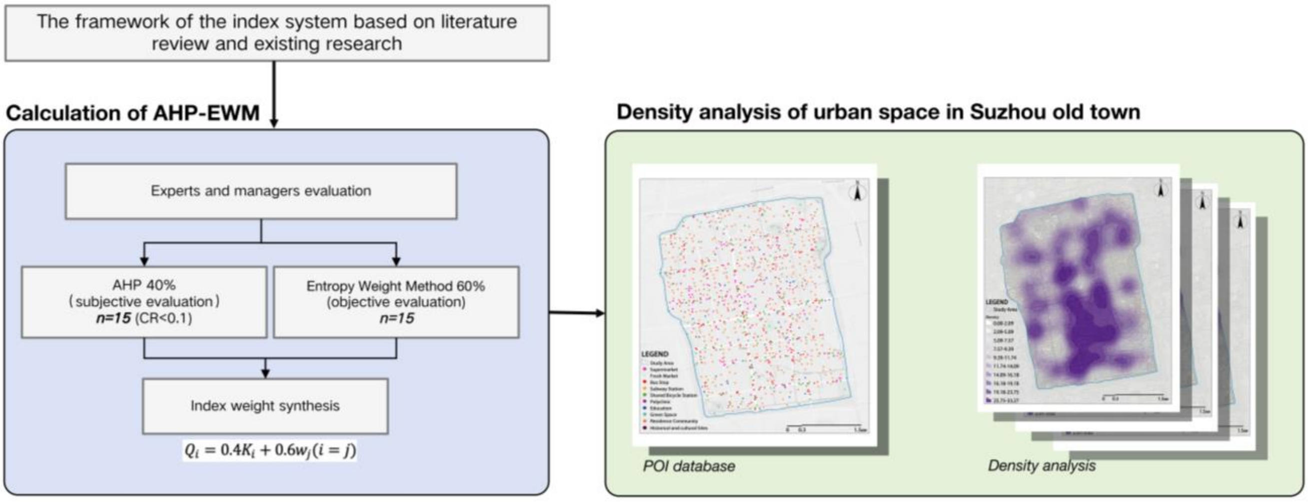

Figure 4. Analysis steps.

2.4.1. Analytic Hierarchy Process (AHP)

AHP was originally developed by Thomas L. Saaty, an American operations researcher at the University of Pittsburgh, in 1971. AHP decomposes complex decision problems into a hierarchical structure of related factors, enabling quantitative analysis through pairwise comparisons [32]. This method applies multi-criteria hierarchical processing and subjective scoring to determine the relative weights of evaluation factors. By breaking down the system into different levels and synthesizing the results, AHP derives comprehensive weights for the overall objective [33], facilitating a scientifically grounded assessment of the research weights with good operational feasibility [34].

There are two common computational approaches in AHP: the product method and the root method, with minimal differences in results. This study employs the root method (geometric mean) to calculate and analyze the results from Expert Questionnaire 1. The AHP procedure requires pairwise comparisons between criteria and indicator levels (Tables 4 and 5), quantified using the nine-point scale.

Table 4. Methodology for the construction of the expert questionnaire 1's criterion layers (B).

Objective (A)	Criterion Layer B1	Criterion Layer B2	Criterion Layer B3	...	Criterion Layer Bn
Criterion layer B1	a11	a12	a 13	...	a1n
Criterion layer B2	a21	a22	a23	...	a2n
Criterion layer B3	a31	a32	a33	...	a3n
...	...	...	...	...	...
Criterion layer Bn	an1	an2	an3	...	ann

Table 5. Methodology for the construction of the expert questionnaire 1's index layers (C).

Criterion Layer (Bn)	Index C1	Index C2	Index C3	...	Index Cn
Index C1	b11	b12	b13	...	b1n
Index C2	b21	b22	b23	...	b2n
Index C3	b31	b32	b33	...	b3n
...	...	...	...	...	...
Index Cn	bn1	bn2	bn3	...	bnn

The judgment matrices for Expert Questionnaire 1 were constructed using Equation (1). The evaluation data from the questionnaire were processed following Equation (2) through

Equation (5) to obtain the subjective evaluation results of each factor [35]. Additionally, data consistency was verified using Equations (6)–(8) to ensure the validity of all collected data.

$$a_{ij} = \begin{cases} a_i - a_j + 1, & (a_i > a_j) \\ 1, & (a_i = a_j) \\ \frac{1}{(a_j - a_i + 1)}, & (a_i < a_j) \end{cases} \tag{1}$$

$$M_i = \prod_{j=1}^{n} a_{ij} (i = 1, 2, \ldots, n) \tag{2}$$

$$w_i = \sqrt[n]{M_i} (i = 1, 2, \ldots, n) \tag{3}$$

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{4}$$

$$K_i = W_{i(\mathrm{B})} \times W_{i(\mathrm{C})} \tag{5}$$

$$l_{max} = \sum_{i=1}^{n} \frac{(AW)_i}{nW_i} \tag{6}$$

$$CI = \frac{l_{max} - n}{n - 1} \tag{7}$$

$$CR = \frac{CI}{RI} \tag{8}$$

In the equations, A represents the constructed judgment matrix, a_i represents the importance scale value of the element B_i, where a_{ij} denotes the value at the ith row and jth column, reflecting the relative importance of element B_i compared to B_j with respect to the target criterion A. The term M_i refers to the product of all elements in the ith row of the judgment matrix. w_i is the geometric mean (i.e., the nth root of M_i), and W_i denotes the normalized weight of the corresponding element at the same hierarchical level. $W_{i(B)}$ means criterion layer's weight and $W_{i(C)}$ means index layer's weight. K_i represents the global weight of the indicator across the hierarchy.

To ensure consistency in the expert judgments, the maximum eigenvalue λ_{max} of the judgment matrix is calculated. The consistency index (CI) and the Consistency Ratio (CR) are computed using the following formulas. The random index (RI) is used as a reference value, as shown in Table 6. A consistency check is considered valid when the CR value is less than 0.1, indicating acceptable consistency among expert judgments [36].

Table 6. Random consistency indexes (*RI* values) for judgment matrices of order 1 to 9.

n	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

2.4.2. The Entropy Weight Method (EWM)

EWM originally derived from the concept of entropy in thermodynamics, serves as a quantitative measure of disorder and uncertainty within a system. In the context of multi-criteria evaluation, EWM reflects the degree of information dispersion and is often employed to determine objective indicator weights based on the variability of data. This method emphasizes the intrinsic relationships among data rather than subjective judgment, thereby enhancing the objectivity of the evaluation outcomes [37]. According to entropy theory, the greater the variability of a particular indicator across the evaluated entities, the more information it conveys, leading to a lower entropy value and thus a higher assigned weight. Conversely, if an indicator exhibits little variation, its entropy value increases, implying less useful information and a correspondingly lower weight [38]. Suppose there are m experts assessing n indicators, the data matrix B is structured as follows:

$$B = \left(b_{ij}\right)_{nm} = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{1m} & b_{2m} & \cdots & b_{nm} \end{bmatrix} \tag{9}$$

Step 1: Normalization of the Data Matrix

To ensure comparability among different indicators, the initial evaluation matrix $B = (b_{ij})_{nm}$, where b_{ij} denotes the score assigned by the ith expert to the jth indicator, must be normalized. The range method is adopted for standardization. When the indicator is positively oriented (i.e., the higher the score, the better the performance), the normalized value c_{ij} is calculated as follows:

$$c_{ij} = \frac{b_{ij} - min\left(b_{ij}\right)}{max\left(b_{ij}\right) - min\left(b_{ij}\right)} \tag{10}$$

When b_{ij} is a negative indicator:

$$c_{ij} = \frac{max\left(b_{ij}\right) - b_{ij}}{max\left(b_{ij}\right) - min\left(b_{ij}\right)} \tag{11}$$

Let b_{ij} represent the observed value of the jth indicator for the ith evaluation object. After normalization (as described in step 1), the standardized value is denoted by c_{ij}, and max(b_{ij}) and min(b_{ij}) refer to the maximum and minimum values of indicator b_{ij} across all evaluation objects, respectively.

Step 2: Calculation of Indicator Proportions

The proportion of the jth indicator for the ith object, P_{ij} is computed as:

$$P_{ij} = \frac{c_{ij}}{\sum_{i=1}^{n} c_{ij}}, (i = 1, 2, \ldots, n; j = 1, 2, \ldots, m) \tag{12}$$

- P_{ij} denotes the normalized proportion of the j-th indicator for the i-th object;
- c_{ij} is the standardized score derived from Step 1.

Step 3: Entropy Value Calculation

The entropy value H_j for the jth indicator is calculated to reflect the degree of information disorder:

$$H_j = -\frac{1}{\ln(m)} \times \sum_{i=1}^{n} \left[P_{ij} \times ln\left(P_{ij}\right)\right] \tag{13}$$

- H_j denotes the entropy value of indicator j;
- n is the total number of evaluation objects;
- P_{ij} is the proportion calculated in Equation (12).
- ln is the natural logarithm, which is used to represent information quantity or entropy in information theory.

To ensure mathematical validity, when P_{ij} = 0, the following convention is adopted:

$$\lim_{P_{ij}=0} P_{ij} \times \ln(P_{ij}) = 0 \tag{14}$$

This avoids undefined values in the entropy computation due to logarithmic operations on zero.

Step 4: Calculation of Objective Weights

Based on the entropy values, the objective weight w_j for each indicator j is calculated using the following formula:

$$w_j = \frac{(1 - H_j)}{\sum_{j=1}^{m} (1 - H_j)} \tag{15}$$

- w_j denotes the objective weight of the jth indicator;
- m represents the number of indicators.

This step allows indicators with greater informational contribution (i.e., lower entropy) to receive higher weights, thereby enhancing the objectivity of the overall evaluation system.

2.4.3. Comprehensive Weight Construction of AHP–EWM

AHP is characterized by subjective weighting, in which decision-makers assign relative importance to each pair of secondary indicators under a specific criterion layer based on their professional knowledge, experience, and contextual understanding. This pairwise comparison process results in a weight distribution that inherently reflects the evaluators' subjective judgment. While this approach allows for nuanced and expert-driven prioritization, it inevitably lacks objectivity and may be influenced by individual bias.

In contrast, EWM provides an objective weighting scheme by leveraging the statistical dispersion of data. Based on the principle of entropy from information theory, EWM calculates indicator weights according to the variability of indicator values across the sample set. The more dispersed the values of an indicator, the more informative it is deemed to be, and hence, the greater its assigned weight. Despite its strong mathematical foundation, EWM is heavily dependent on the sample size and data quality. It fails to account for the contextual significance of indicators as perceived by experts or stakeholders, which can occasionally lead to results that diverge from practical expectations.

To mitigate the limitations of both methods and enhance the robustness of the evaluation model, this study integrates the AHP-derived subjective weights with the EWM-derived objective weights. Specifically, the EWM is used to revise and calibrate the initial subjective weights generated through the AHP process. By considering the degree of data dispersion, EWM adjusts the original weight distribution to enhance objectivity without discarding expert insight. The combined weighting approach aims to strike a balance between professional judgment and data driven accuracy, thereby constructing a more stable and comprehensive evaluation framework for urban spatial adaptability in the context of SAVs.

$$Q = aw^1 + (1 - a)w^2 \tag{16}$$

Let Q, as defined in Equation (16) denote the final integrated weight, where w^1 represents the subjective weight obtained through the AHP, and w^2 represents the objective weight derived from the EWM. To balance the influence of subjective judgment and objective data, a proportion coefficient α is introduced, where $0 \leq \alpha \leq 1$. The value of α is determined by the researcher based on the specific context of this study and through consultation with domain experts.

Referring to commonly adopted compromise coefficients in existing studies and expert recommendations, this study adopts a coefficient value of α = 0.4 [25]. The composite weight Q_i is then calculated using the following formula:

$$Q_i = 0.4K_i + 0.6w_j(i = j) \tag{17}$$

In Equation (17), K_i represents the weight calculated by AHP (Equation (5)), w_j represents the weight calculated by EWM (Equation (15)), and $I = j$ indicates that the calculation results are for the same indicator.

2.4.4. ArcGIS GeoPlanner

ArcGIS GeoPlanner, 3.8.1 a rapid geodesign tool, was employed to analyze the spatial density of Suzhou old town based on relevant Point of Interest (POI). This urban planning tool is known for its simplicity and ease of use, enabling efficient planning and practical application (see Figure 5). Its user friendly input and output interfaces provide a flexible and effective design platform for urban planners and related professionals [24].

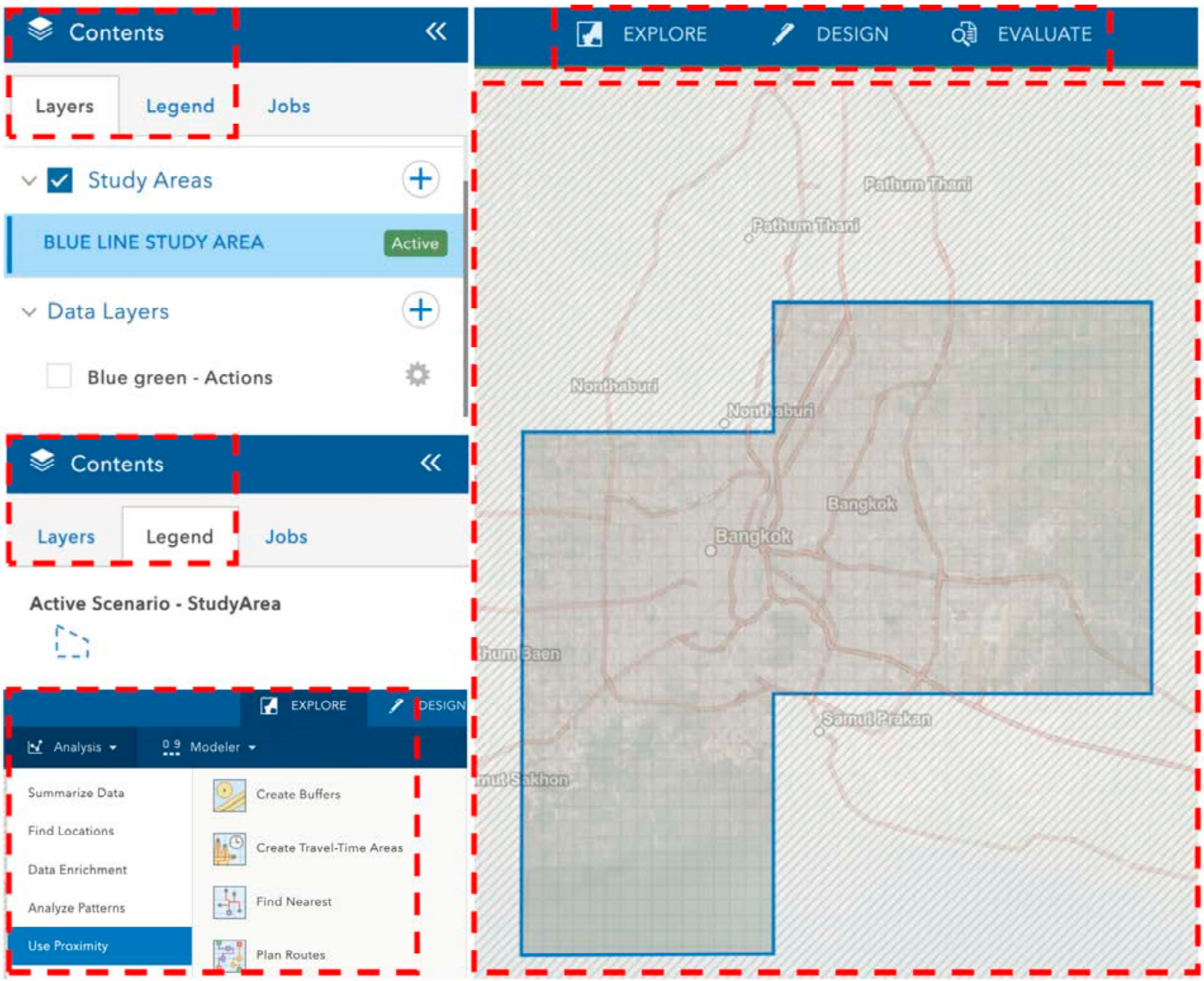

Figure 5. ArcGIS GeoPlanner operation interface.

Based on the results of the AHP–EWM evaluation, governmental planning documents, and remote sensing (RS) data, relevant POI for the old town urban space were identified. A spatial density analysis of Suzhou old town was conducted to assist in evaluating the potential impacts of SAVs on the local urban space.

To ensure the reproducibility and transparency of the research, the types, sources and purposes of the involved data are shown in the Table 7:

Table 7. Data type, source and purpose.

Types of Data	Data Source Platform	Unit of Analysis	Purpose of Using
Experts' questionnaire	Online and offline	Expert unit	Perceive the weight of expert perspective elements.
Function of land use	OpenStreetMap	Area unit	The current situation of land function utilization in Suzhou old town.
POI database	OpenStreetMap	Area unit	Identification of user-related urban service density.
Policy atlas	Government official website	Area unit	There is currently a special planning for the protection of Suzhou old town.

2.5. Samples

This section outlines the composition and setting reasons of the participants involved in expert evaluation processes.

Expert Questionnaire 1: Based on previous studies, it is generally accepted that involving 5 to 15 experts in AHP analyses provides a balance between data quality and decision making reliability. For instance, Zhu et al. invited 15 experts to evaluate aging friendly facilities in public spaces of old residential communities using the AHP method [37], while Li employed 14 experts to assess 30 rural human settlement indicators [38]. Following these precedents, this study recruited 15 experts to complete Expert Questionnaire 1.

Expert Questionnaire 2: Drawing on prior research experience, studies using the EWM, particularly those involving multidisciplinary and cross sectoral evaluations, typically engage more than ten experts. Zhu et al. also employed 15 experts for the EWM-based evaluation of aging friendly facilities in public spaces [36]. Accordingly, this study recruited 15 experts to complete Expert Questionnaire 2.

Expert Panel 1 (for Questionnaire 1): A total of 15 experts were invited, with disciplinary backgrounds spanning urban planning (3 experts), transportation engineering (2), intelligent mobility (2), architectural design (2), landscape architecture (2), art and aesthetics (2), and government decision making and administration (2). Each expert had at least ten years of relevant professional experience and had lived in Suzhou for over one year.

Expert Panel 2 (for Questionnaire 2): Similarly, 15 experts were invited for the second questionnaire, covering the same seven domains: urban planning (3 experts), transportation engineering (2), intelligent mobility (2), architectural design (2), landscape architecture (2), art and aesthetics (2), and government decision making and administration (2). All experts had at least ten years of relevant experience and had resided in Suzhou for more than one year.

Experts settings are based on three dimensions: spatial, technology, and policy, as shown in Table 8.

Table 8. Dimension of experts.

Dimension	Choice of Experts
Spatial dimension	Urban Planning, Architectural Design, Landscape Architecture, Art and Aesthetics
Technological dimension	Transportation Engineering, Intelligent Mobility Systems
Policy dimension	Government Policy and Urban Management

It should be noted that Expert Panels 1 and 2 consisted of different individuals to ensure diverse perspectives and avoid response bias.

While the sample size may appear relatively small, it is consistent with standard practices in related expert surveys [39]. Recent studies have employed similar or smaller expert groups to ensure methodological rigor while maintaining manageability and consistency in judgment aggregation [40]. These precedents suggest that the current sample size is appropriate for this study's objectives and analytical framework.

Nevertheless, this study acknowledges that the number and diversity of expert perspectives can influence the robustness of multi-criteria decision-making models. Future studies could expand the expert panel to include a broader cross-section of stakeholders, such as policymakers, mobility providers, or residents with technical backgrounds, to further validate and enrich the weighting process.

2.6. Consistency Test of the Questionnaire

The results of Expert Questionnaire 1 were evaluated using the AHP, and a consistency test was conducted to verify the validity of the collected data. The Consistency Ratio (CR) was used as the primary indicator; a CR value less than 0.1 indicates that the pairwise comparison matrix meets the consistency requirement and the calculated weights are logically valid and acceptable for further analysis [35].

2.7. Ethical Considerations

This study has received ethical approval from the Institutional Review Board (IRB) of King Mongkut's University of Technology Thonburi. The approved protocol number is KMUTT-IRB-COE-2025-044.

Participants: All participants in this study, including experts and residents (both urban and rural), are non-disabled adults over the age of 18. No vulnerable populations were involved in this study.

Data Anonymization: All interview transcripts and questionnaire responses were fully anonymized to ensure the privacy and confidentiality of participants.

Participant Information Sheet: During the data collection phase, each participant received a Participant Information Sheet, which clearly explained the purpose of this study, the time required, potential risks, and how the data would be used and stored.

3. Results

This chapter presents the empirical findings from expert-based weighting analysis and spatial data evaluation. By integrating the results of the AHP–EWM weighted assessment with POI density analysis, it systematically explores how SAVs technology may potentially reshape the spatial configuration of Suzhou old town.

Both Expert Questionnaire 1 and Expert Questionnaire 2 were distributed via the online platform Sojump, targeting experts who met the predefined selection criteria.

Expert Questionnaire 1 was administered between 5 June and 10 June 2025, and a total of 15 valid responses were collected.

Expert Questionnaire 2 was conducted between 19 March and 30 May 2025, also yielding 15 valid responses.

All participants were invited based on their domain expertise and relevance to the study objectives, and were informed about the research content and confidentiality protocols before participation.

3.1. AHP Weight Calculation Results

Based on the requirements of the evaluation model, 15 experts evaluated the relative importance of each criterion and sub-criterion through pairwise comparisons. The calculated weights of the criterion layer are presented in Table 9, while the weights of the index layer are presented in Tables 10–14.

Table 9. Judgment matrix of the criterion layer to the objective layer (A1).

A1 The living Environment, Travel Experience and Spatial Quality Demands of the Residents in Old Town	B1 Influencing Factors of Residential Area Selection	B2 The Daily Functional Space Requirements of Old Town	B3 Perception of the Environmental Quality of Traffic Space in the Old Town	B4 Dimension of SAVs Service Quality Sense	B5 The Accessibility Requirements of Multi-Functional Urban Spaces	Weight (W_i)
B1 Influencing factors of residential area selection	1	0.420	0.941	1.399	0.827	0.1652
B2 The daily functional space requirements of old town	2.380	1	1.099	1.511	0.965	0.2526
B3 Perception of the environmental quality of traffic space in the old town	1.062	0.910	1	1.446	1.199	0.2143
B4 Dimension of SAVs service quality sense	0.715	0.662	0.691	1	0.318	0.1229
B5 The accessibility requirements of multi-functional urban spaces	1.209	1.036	0.834	3.142	1	0.2450
Consistency Check	CI = 0.037; CR = 0.033					Meet the Requirements

Table 10. Judgment matrix of the index layer to the criterion layer (B1).

B1 Influencing Factors of Residential Area Selection	C1 Residential Convenience of Travel	C2 Residential Prices	C3 Residential Environment	C4 Accessibility of Residential Areas	Weight (W_i)
C1 Residential Convenience of Travel	1	0.386	0.721	0.608	0.1546
C2 Residential Prices	2.589	1	1.015	1.348	0.3306
C3 Residential Environment	1.387	0.985	1	1.227	0.2742
C4 Accessibility of Residential Areas	1.645	0.742	0.815	1	0.2406
Consistency Check	CI = 0.011; CR = 0.013				Meet the Requirements

Table 11. Judgment matrix of the index layer to the criterion layer (B2).

B2 The Daily Functional Space Requirements of Old Town	C5 Availability of Parking Space	C6 Urban Fitness Spaces	C7 Park and Green Spaces	Weight (W_i)
C5 Availability of Parking Space	1	1.311	0.725	0.318
C6 Urban Fitness Spaces	0.763	1	0.538	0.240
C7 Park and Green Spaces	1.380	1.858	1	0.442
Consistency Check	CI = 0.000; CR = 0.000			Meet the Requirements

Table 12. Judgment matrix of the index layer to the criterion layer (B3).

B3 Perception of the Environmental Quality of Traffic Space in the Old Town	C8 Aesthetic and Personalized Design of Transportation Facilities	C9 Number of Traffic Barriers and Traffic Lights in Old Town	C10 Density of PUDO Points in Old Town	C11 Density of Public Transport Stops in Old Town	C12 Barrier-Free Transportation Facilities in Old Town	C13 Density of Gasoline and Charging Stations	C14 Air Quality and Noise	Weight (W_i)
C8 Aesthetic and Personalized Design of Transportation Facilities	1	0.448	0.697	0.239	0.260	0.987	0.436	0.0660

Table 12. *Cont.*

B3 Perception of the Environmental Quality of Traffic Space in the Old Town	C8 Aesthetic and Personalized Design of Transportation Facilities	C9 Number of Traffic Barriers and Traffic Lights in Old Town	C10 Density of PUDO Points in Old Town	C11 Density of Public Transport Stops in Old Town	C12 Barrier-Free Transportation Facilities in Old Town	C13 Density of Gasoline and Charging Stations	C14 Air Quality and Noise	Weight (W_i)
C9 Number of Traffic Barriers and Traffic Lights in Old Town	2.234	1	0.387	0.476	0.505	1.433	0.321	0.0934
C10 Density of PUDO Points in Old Town	1.434	2.583	1	0.926	0.926	1.650	0.506	0.1502
C11 Density of Public Transport Stops in Old Town	4.193	2.101	1.080	1	1.291	1.511	0.652	0.1866
C12 Barrier-Free Transportation Facilities in Old Town	3.845	1.981	1.080	0.775	1	1.517	0.487	0.1630
C13 Density of Gasoline and Charging Stations	1.013	0.698	0.606	0.662	0.659	1	0.508	0.0933
C14 Air Quality and Noise	2.293	3.115	1.975	1.533	2.055	1.968	1	0.2475
Consistency Check				CI = 0.046; CR = 0.035				Meet the Requirements

Table 13. Judgment matrix of the index layer to the criterion layer(B4).

B4 Dimension of SAVs Service Quality Sense	C15 Travel Cost	C16 Travel Safety	C17 Social Needs During Travel	C18 Travel Efficiency	Weight (W_i)
C15 Travel Cost	1	0.21	1.836	1.323	0.1798
C16 Travel Safety	4.768	1	2.596	2.872	0.5194
C17 Social Needs During Travel	0.545	0.385	1	0.549	0.1239
C18 Travel Efficiency	0.756	0.348	1.821	1	0.1769
Consistency Check			CI = 0.056; CR = 0.063		Meet the Requirements

Table 14. Judgment matrix of the index layer to the criterion layer (B5).

B5 The Accessibility Requirements of Multi-Functional Urban Spaces	C19 Accessibility to Suburban Scenic Spots	C20 Accessibility to Transportation Hubs	C21 Accessibility to Cultural and Sports Spaces for Residents	C22 Comprehensive Accessibility in Old Town	Weight (W_i)
C19 Accessibility to Suburban Scenic Spots	1	0.247	0.440	0.940	0.1315
C20 Accessibility to Transportation Hubs	4.042	1	1.060	1.565	0.3744
C21 Accessibility to Cultural and Sports Spaces for Residents	2.271	0.944	1	1.075	0.2867
C22 Comprehensive Accessibility in Old Town	1.063	0.639	0.930	1	0.2074
Consistency Check			CI = 0.034; CR = 0.038		Meet the Requirements

A consistency check was conducted on all judgment matrices. The results showed that all Consistency Ratios (*CR*) were less than 0.1, indicating that the expert judgments were consistent and the derived weights are valid and reliable.

The AHP calculation yielded the weights of each criterion layer and their corresponding indexes. The local weights (within the same level) can be used to compare the relative importance of indicators within each criterion layer, while the global weights reflect the relative importance of all evaluation indicators across the entire framework. The computed weights of all evaluation indicators are presented in Tables 9–14.

3.2. EWM Weight Calculation Results

The importance ratings of each criterion layer indicator provided by 15 experts were standardized, and the normalized scores are shown in Figure 6. Since all indicators used in this study are positively oriented, normalization was performed using Equation (10). Subsequently, the information entropy and weights of each indicator were calculated using Equations (11)–(14).

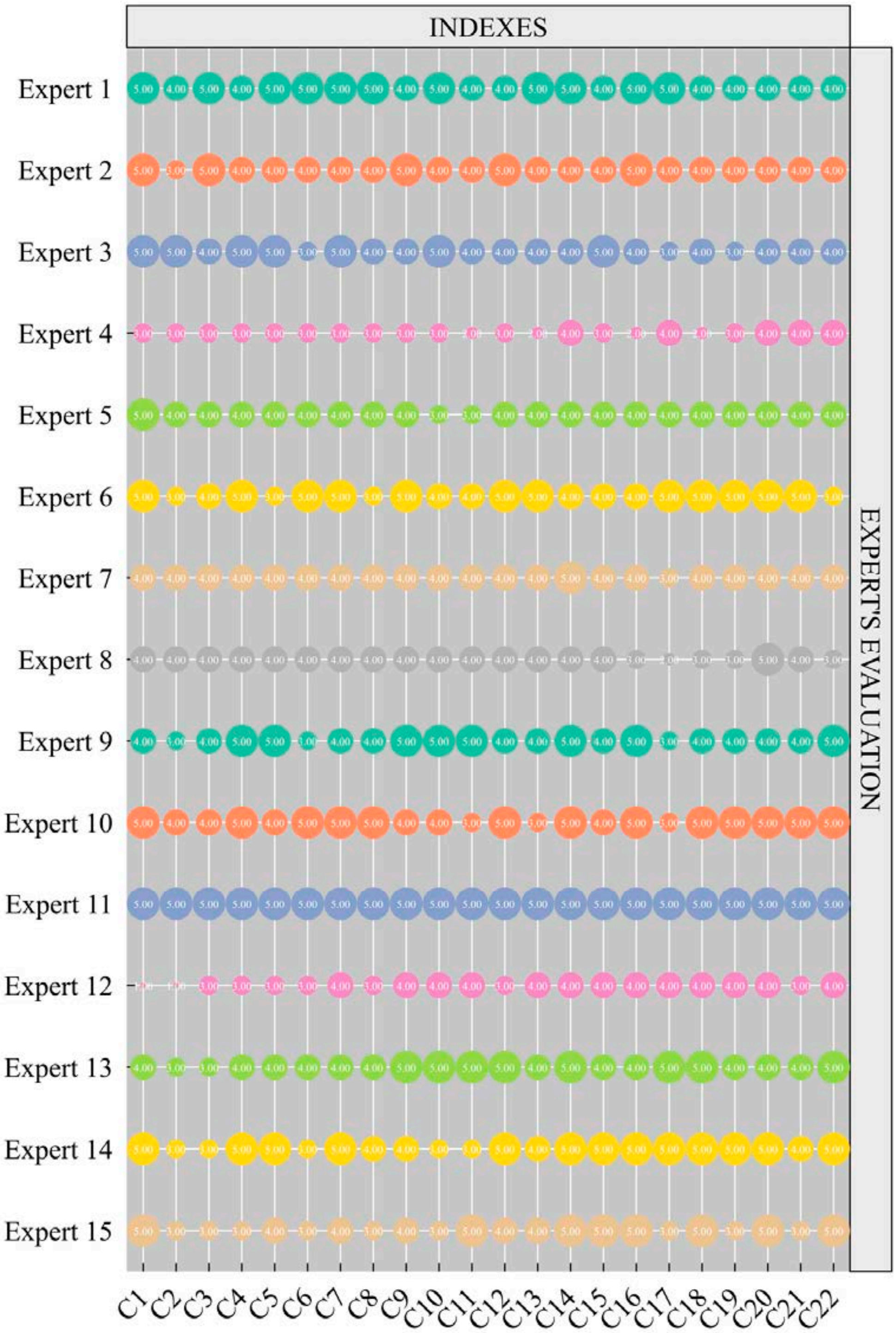

Figure 6. EWM scoring bubble plot.

3.3. Integrated Weight Calculation Using AHP–EWM

The results obtained from the AHP and EWM were incorporated into Equation (17) to derive the adjusted weights for each evaluation indicator (Figure 7). By integrating the subjective demand-based weights from AHP with the objective data driven weights from EWM, the resulting composite weights offer a more balanced and objective representation. The final corrected weights of the indicators are presented (Table 15).

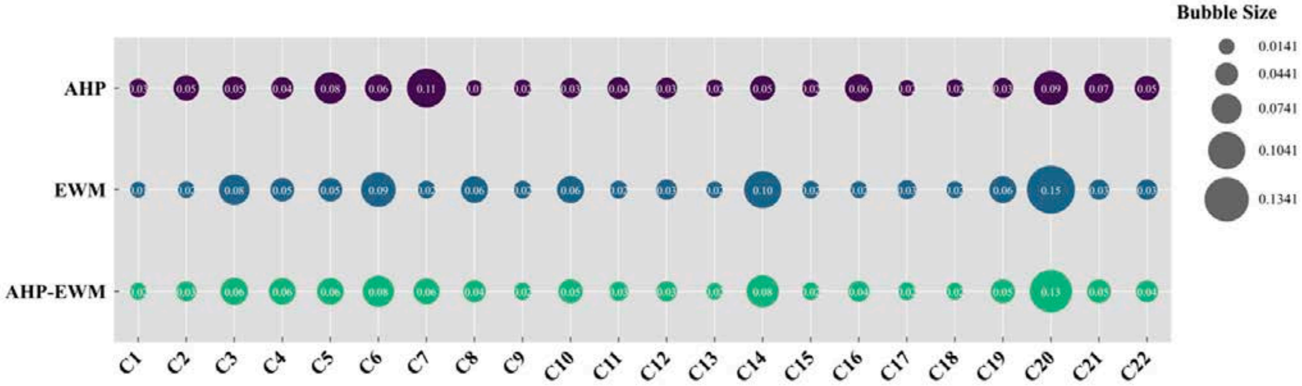

Figure 7. Comparison of AHP weight, EWM weight, and AHP–EWM weight.

Table 15. AHP weight, EWM weight and AHP–EWM weight.

AHP					EWM		AHP–EWM	
Criterion Layer (B)	**Criterion Layer Weight ($w_{i(B)}$)**	**Index Layer (C)**	**Index Layer Weight ($w_{i(C)}$)**	**Subjective Weight (K_i)**	**Information Entropy (Hj)**	**Objective Weight (w_j)**	**Comprehensive Weight (Q_i)**	**Comprehensive Weight Ranking**
B1 Influencing factors of residential area selection	0.1652	C1 Residential Convenience of Travel	0.1546	0.0255	0.9702	0.0145	0.0189	21
		C2 Residential Prices	0.3306	0.0546	0.9638	0.0176	0.0324	15
		C3 Residential Environment	0.2742	0.0453	0.8442	0.0759	0.0637	4
		C4 Accessibility of Residential Areas	0.2406	0.0397	0.9038	0.0469	0.0440	10
B2 The daily functional space requirements of old town	0.2526	C5 Availability of Parking Space	0.318	0.0803	0.9031	0.0472	0.0605	5
		C6 Urban Fitness Spaces	0.24	0.0606	0.8081	0.0935	0.0803	3
		C7 Park and Green Spaces	0.442	0.1116	0.9552	0.0218	0.0577	6
B3 Perception of the environmental quality of traffic space in the old town	0.2143	C8 Aesthetic and Personalized Design of Transportation Facilities	0.066	0.0141	0.8762	0.0603	0.0418	11
		C9 Number of Traffic Barriers and Traffic Lights in Old Town	0.0934	0.0200	0.9552	0.0218	0.0211	19
		C10 Density of PUDO Points in Old Town	0.1502	0.0322	0.8742	0.0613	0.0497	7
		C11 Density of Public Transport Stops in Old Town	0.1866	0.0400	0.9547	0.0221	0.0293	16
		C12 Barrier-Free Transportation Facilities in Old Town	0.163	0.0349	0.9303	0.0339	0.0343	14
		C13 Density of Gasoline and Charging Stations	0.0933	0.0200	0.9659	0.0166	0.0180	22
		C14 Air Quality and Noise	0.2475	0.0530	0.7857	0.1044	0.0839	2

Table 15. *Cont.*

	AHP				EWM		AHP–EWM	
Criterion Layer (B)	Criterion Layer Weight ($w_{i(B)}$)	Index Layer (C)	Index Layer Weight ($w_{i(C)}$)	Subjective Weight (K_i)	Information Entropy (Hj)	Objective Weight (w_j)	Comprehensive Weight (Q_i)	Comprehensive Weight Ranking
B4 Dimension of SAVs service quality sense	0.1229	C15 Travel Cost	0.1798	0.0221	0.9563	0.0213	0.0216	18
		C16 Travel Safety	0.5194	0.0638	0.9634	0.0178	0.0362	13
		C17 Social Needs During Travel	0.1239	0.0152	0.9431	0.0277	0.0227	17
		C18 Travel Efficiency	0.1769	0.0217	0.9634	0.0178	0.0194	20
B5 The accessibility requirements of multi-functional urban spaces	0.245	C19 Accessibility to Suburban Scenic Spots	0.1315	0.0322	0.8743	0.0612	0.0496	8
		C20 Accessibility to Transportation Hubs	0.3744	0.0917	0.692	0.1500	0.1267	1
		C21 Accessibility to Cultural and Sports Spaces for Residents	0.2867	0.0702	0.9331	0.0326	0.0477	9
		C22 Comprehensive Accessibility in Old Town	0.2074	0.0508	0.9303	0.0338	0.0406	12

The integrated weights derived from the combination of AHP and EWM systematically reveal the prioritization of residents' demands regarding the living environment, travel experience, and spatial quality in the context of SAVs integration into old towns (Figure 8).

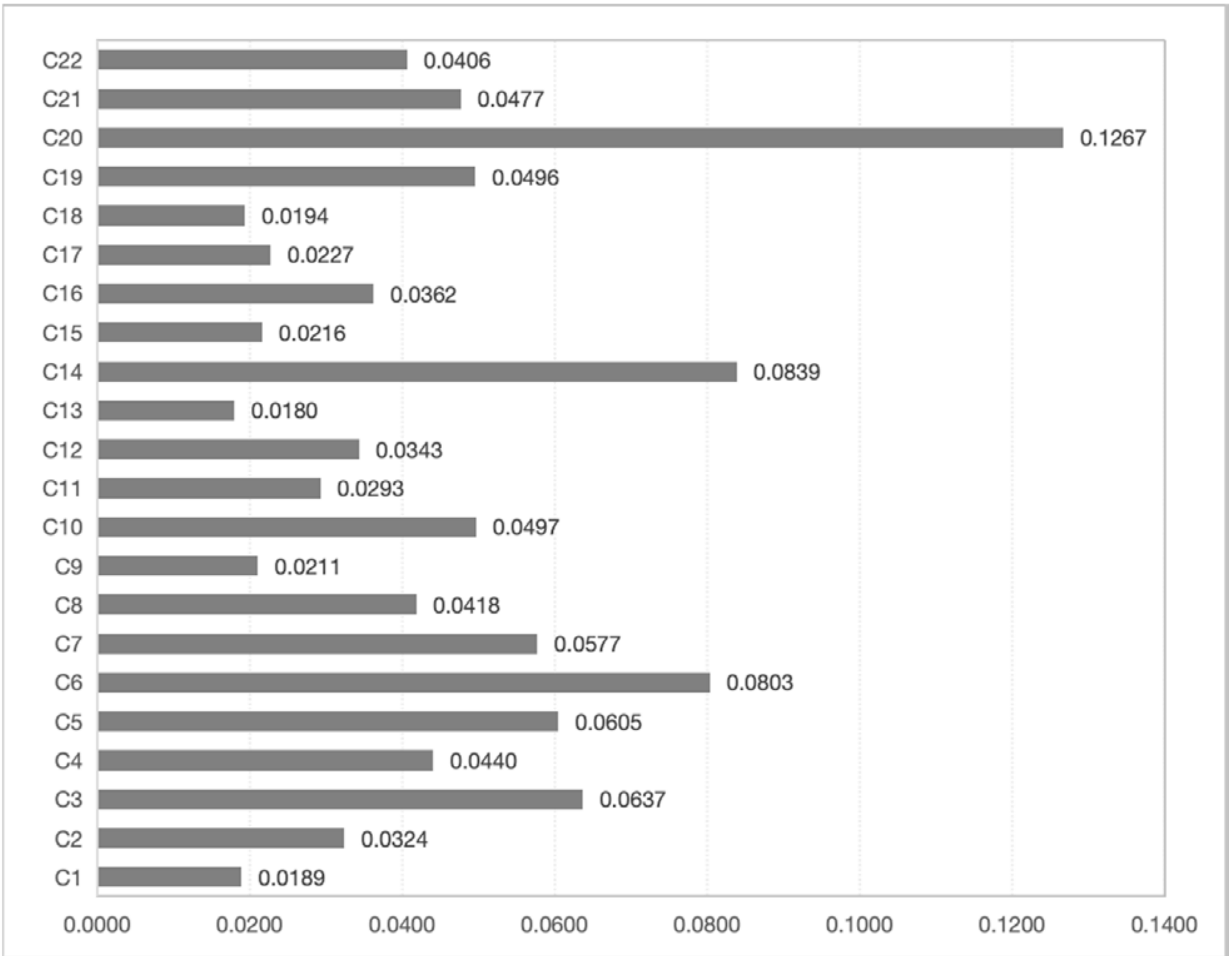

Figure 8. AHP–EWM specific weights of each indexes layers (C).

The results indicate that C20: Accessibility to Transportation Hubs holds the highest comprehensive weight (0.1267), significantly exceeding other indicators at the same hierarchical level. This suggests that proximity to major transportation nodes is considered the most critical factor in spatial renewal strategies under SAVs application.

C14: Air Quality and Noise, C6: Urban Fitness Spaces, C3: Residential Environment, and C5: Availability of Parking Space rank second to fifth, reflecting the increasing concern for environmental quality, public health infrastructure, and functional residential support facilities.

Indicators such as C7: Park and Green Spaces, C10: Density of PUDO Points in Old Town, C19: Accessibility to Suburban Scenic Spots, C21: Accessibility to Cultural and Sports Spaces for Residents, C4: Accessibility of Residential Areas, C8: Aesthetic and Personalized Design of Transportation Facilities, C22: Comprehensive Accessibility in Old Town, C16: Travel Safety, C12: Barrier-Free Transportation Facilities in Old Town, and C2: Residential Prices fall within the medium priority range, ranking from sixth to fifteenth.

Finally, C11: Density of Public Transport Stops in Old Town, C17: Social Needs During Travel, C15: Travel Cost, C9: Number of Traffic Barriers and Traffic Lights in Old Town, C18: Travel Efficiency, C1: Residential Convenience of Travel, and C13: Density of Gasoline and Charging Stations are positioned in the lower priority range, occupying the sixteenth to twenty second positions.

These findings highlight differentiated attention levels across spatial, environmental, and mobility related indicators in old town areas, offering targeted insights for urban regeneration strategies aligned with SAVs integration.

3.4. Current Spatial Condition Analysis of Suzhou Old Town

To examine the spatial distribution characteristics of key urban elements and facilities within Suzhou old town, this study applies kernel density analysis to visualize the concentration patterns of nine categories of critical POI. These include:

- Bus Stops;
- Subway Stations;
- Shared Bicycle Stations;
- Educational Areas;
- Supermarkets and Fresh Markets;
- Polyclinics;
- Historic and Cultural Spaces;
- Residential Areas;
- Green Spaces.

The analysis aims to reveal the spatial structure and functional layout of Suzhou old town, providing empirical evidence to support the evaluation of spatial adaptability in the context of SAVs. By identifying the high-density clusters and spatial voids of these POI categories, this approach offers insights into the accessibility, service coverage, and land use efficiency of different urban functions, thereby informing targeted urban regeneration strategies and transport infrastructure planning under the SAVs paradigm (Figure 9).

From the overall bar chart data, it is evident that Figure 10b Subway Station Density and Figure 10f Polyclinic Density exhibit localized gaps in spatial coverage, failing to adequately serve the entire spatial extent of Suzhou old town. This indicates a spatial mismatch between infrastructure distribution and urban demand in these two categories. In contrast, the density distribution of the remaining POI (Bus Stops, Shared Bicycle Stations, Educational Areas, Supermarkets and Fresh Markets, Historic and Cultural Spaces, Residential Areas, and Green Spaces) appears more spatially uniform and balanced across the study area. This suggests a relatively well developed urban service network in terms of everyday life and mobility support, with potential for integration into future SAVs applications. Addressing the deficiencies in public transit nodes and health service facilities may be crucial for achieving a more inclusive and accessible urban environment in the context of smart mobility transitions (Figure 10).

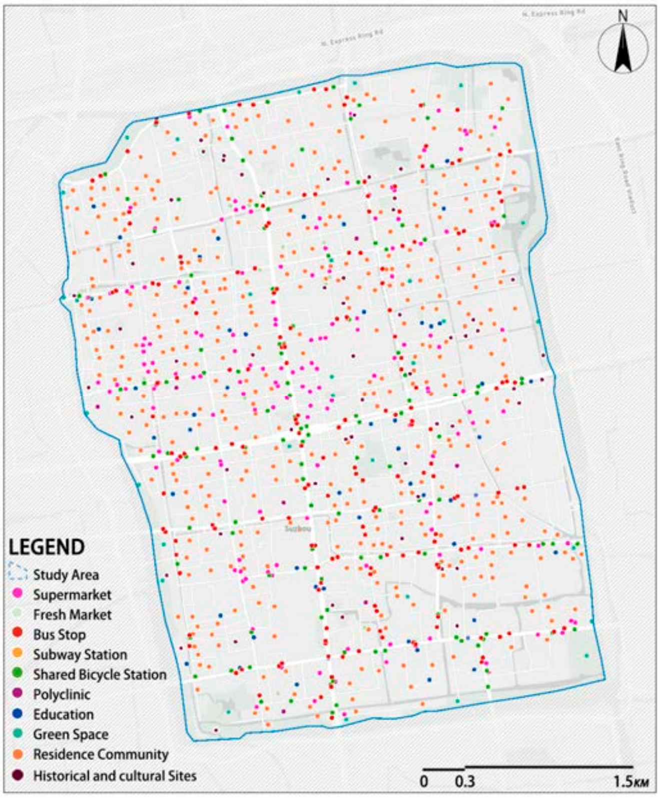

Figure 9. POI map of Suzhou old town.

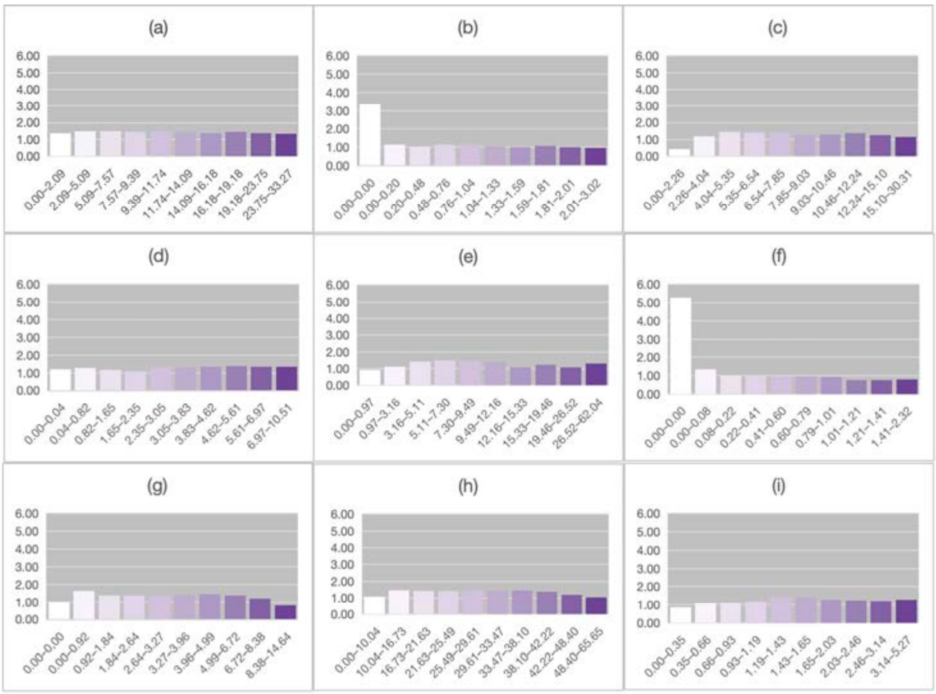

Figure 10. Comparison of data from density analysis of different urban spaces in Suzhou old town: (**a**) Bus Stop Density, (**b**) Subway Station Density, (**c**) Shared Bicycle Station Density, (**d**) Educational Area Density, (**e**) Supermarket and Fresh Market Density, (**f**) Polyclinic Density, (**g**) Historic and Cultural Space Density, (**h**) Residence Density, and (**i**) Green Space Density.

Based on the POI density analysis, the spatial distribution is visualized in Figure 11 as follows (Figure 11):

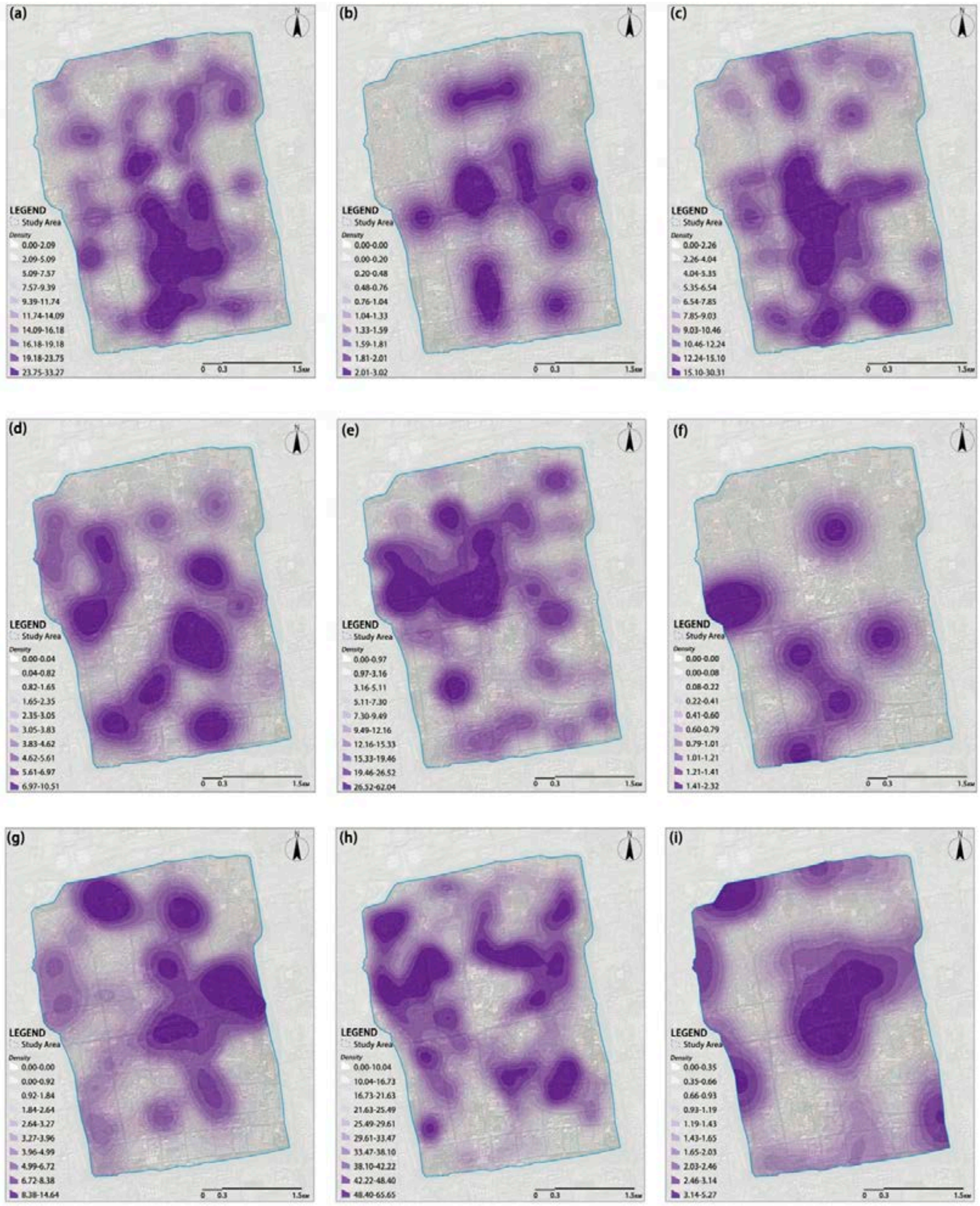

Figure 11. Results from density analysis of different urban spaces in Suzhou old town: (**a**) Bus Stop Density, (**b**) Subway Station Density, (**c**) Shared Bicycle Station Density, (**d**) Educational Area Density, (**e**) Supermarket and Fresh Market Density, (**f**) Polyclinic Density, (**g**) Historic and Cultural Space Density, (**h**) Residence Density, and (**i**) Green Space Density.

(a) Bus Stop Density: Bus stops exhibit a polycentric distribution pattern, with an overall balanced spatial layout. The hotspot areas are primarily concentrated in the south central part of the Old Town, where public transportation coverage is relatively high, effectively meeting the commuting needs of residents across a broad area. However, the southeastern, northeastern, and northwestern corners of the Old Town show sparse bus stop coverage.

(b) Subway Station Density: The overall density of subway stations in Suzhou old town is low, with hotspots mainly located in the central area, corresponding to tourist attractions and major commercial zones. The density values are significantly lower compared to bus stops, indicating an underdeveloped rail transit network that limits improvements in regional accessibility.

(c) Shared Bicycle Station Density: The distribution of shared bicycle stations is relatively balanced, though with noticeable density variations. High-density hotspots overlap spatially with bus stop clusters in the central and south central areas. This pattern facilitates shared bicycles as an effective last-mile connector supplementing public transit within these zones.

(d) Educational Area Density: Educational facilities are distributed in multiple small, clustered cores, with concentrated hotspots. Conversely, the northern, western, and southeastern parts of the Old Town show lower densities, potentially increasing travel demand for students in these areas.

(e) Supermarket and Fresh Market Density: Living service facilities form a high-density core around the middle of the Old Town, significantly exceeding surrounding areas and creating a distinct commercial cluster. However, the southern part of the Old Town exhibits relatively insufficient density of such facilities.

(f) Polyclinic Density: Comprehensive healthcare service points concentrate mainly in the western and southern parts of the Old Town, with weaker presence elsewhere—particularly in the southeastern and northwestern areas. This spatial disparity may lead to increased travel distances for medical care and reduced accessibility to health services in those underserved zones.

(g) Historic and Cultural Space Density: Numerous historic and cultural blocks exist within Suzhou old town, with notable aggregation in the central eastern and northeastern sectors. High-density values here reflect the spatial continuity of traditional historical cultural spaces, which serve as key cultural tourism nodes and are vital to the city’s identity and urban landscape.

(h) Residence Density: Residential areas are generally evenly distributed but show some central clustering. High-density residential zones are located primarily in the northwest, northeast, and eastern parts of the Old Town.

(i) Green Space Density: Green spaces mainly concentrate in the northwest central and southeastern parts of the Old Town. Their distribution largely follows the historic city wall and gate layout. However, some residential areas lack sufficient auxiliary green spaces, making the enhancement of public green space density in these zones critical to improving residents’ living environment quality.

4. Discussion

The mobility challenges faced by historic cities primarily stem from the long-standing tension between inherited spatial structures, cultural preservation requirements, and the demands of modern development. In Suzhou old town, issues such as narrow alleyways, uneven infrastructure distribution, and fragmented urban green spaces pose significant urban challenges, particularly limiting mobility opportunities for transportation-disadvantaged groups. Meanwhile, the imperative to preserve cultural heritage further constrains infrastructure upgrades.

4.1. Weight Analysis Based on AHP–EWM

The integrated weighting results from the combined AHP–EWM method reveal that the criterion C20: Accessibility to Transportation Hubs holds a significantly higher composite weight than other indicators at the same hierarchical level, underscoring its central importance in the expert evaluation system. This finding reflects the critical role that transportation node accessibility plays in influencing daily travel quality and urban spatial efficiency within the unique historical, cultural, and residential context of Suzhou old town. Experts consistently emphasized that, in the context of the gradual integration of SAVs into the transportation system, achieving efficient connectivity between the Old Town and major transport hubs—such as subway stations and bus stops—should be a priority in the reorganization of urban traffic systems. This priority not only enhances urban operational efficiency but also profoundly impacts the design of SAV deployment scenarios and their spatial adaptation pathways. The conclusion further validates the dominant role of hub accessibility in travel behavior decision making.

Other top ranking indicators include C14: Air Quality and Noise, C6: Urban Fitness Spaces, C3: Residential Environment, and C5: Availability of Parking Space. The high weights of these indicators reflect the expert panel's strong concern for the comfort and quality of living environments in the Old Town. Notably, under conditions of intense urban development and saturated traffic capacity, traditional residential comfort faces significant challenges—particularly regarding noise pollution, air quality degradation, and insufficient fitness and recreational spaces. These factors have become key determinants of resident satisfaction. Consequently, enhancing the physical and environmental friendliness of SAVs embedded in the urban fabric—such that they not only function as transport means but also contribute to improving urban livability—emerges as an indispensable future planning direction.

Indicators in the medium weight range include C7: Park and Green Spaces, C10: Density of PUDO Points, C19: Accessibility to Suburban Scenic Spots, and C21: Accessibility to Cultural and Sports Facilities. Although these factors do not rank as the highest priorities, their overall scores remain significant, demonstrating that beyond core commuting needs, experts also value the diversification of daily living spaces and functional amenities. This suggests that residents increasingly expect convenience, leisure, and cultural spaces alongside rigid travel demands, especially as SAVs systems hold potential for customized services that may further strengthen attention to flexible spaces such as cultural and green areas.

Low-weight indicators, such as C11: Density of Public Transport Stations, C15: Demand for Social Interaction during Travel, C13: Travel Cost, and C16: Availability of Traditional Infrastructure, score significantly below the average. On one hand, this indicates that experts perceive the public transport resources and infrastructure in Suzhou old town—being the city center—as sufficiently mature and adequate, thus treating these elements as "given conditions" rather than key influencing factors. These basic services are viewed as implicit guarantees rather than direct contributors to satisfaction. On the other hand, the relatively low importance assigned to social interaction during travel reveals a prevailing expert focus on rational dimensions such as efficiency, convenience, and safety in travel experience construction, while affective dimensions like social connectivity receive less emphasis. This is especially relevant in the early stages of SAVs adoption, where enclosed, personalized vehicle environments may reduce stranger interactions, potentially causing a social isolation effect, yet expert sensitivity to this issue remains limited.

Based on the comprehensive expert scoring results, several key conclusions can be drawn:

Hub accessibility as a fundamental attribute holds clear priority. Experts broadly agree that future SAVs systems should prioritize efficient linkage between residents and major urban transport nodes, particularly critical in the high-density context of Old Town.

Weights related to living environment dimensions continue to rise. Air quality, noise control, fitness spaces, and residential environment increasingly serve as important references for urban spatial quality assessment.

Convenience and diversity of living circles constitute secondary but stable expectations. Although cultural, recreational, PUDO density, and suburban access dimensions are not primary focuses, they play essential roles in enhancing urban resilience, cultural atmosphere, and diverse functional experiences.

Sensitivity to traditional infrastructure completeness and economic factors declines, indicating a shift in resident expectations from basic functional demands toward higher travel quality. The relative marginalization of fundamental service elements in evaluation reflects a structural upgrade in public expectations, signaling a transition in urban renewal from basic guarantees to quality enhancement.

From the perspective of spatial justice theory, the current distribution of public service facilities in Suzhou old town reveals significant spatial inequality. The flexible operation of SAVs offers new possibilities for improving accessibility in marginalized areas and among vulnerable populations. Residents in peripheral neighborhoods can break free from the traditional fixed-radius service zones, leading to a rebalancing of service accessibility. This shift (from a facility-centered to a people-centered accessibility paradigm) aligns with the concept of facility accessibility frequently discussed in the spatial justice literature [41]. In comparable historic urban areas, such as the old town of Seville in Spain and the old port district of Hamburg in Germany, traditional walkability-based planning has struggled to meet increasingly diverse daily needs. The integration of SAVs allows for a redistribution of service facilities and promotes a shift in urban spatial resource allocation—from geographic centralization to functional equity.

While this study employed a robust AHP–EWM hybrid model with expert input to assess the relative importance of spatial indicators, it should be noted that the findings are based solely on expert judgments. Residents' actual behaviors, preferences, or acceptance toward SAVs integration were not directly captured. This presents a potential limitation, as there may exist discrepancies between professional perspectives and lived experiences in Suzhou old town.

Future research should incorporate survey data, travel diaries, or behavioral mapping of local residents and travelers to triangulate the results and refine planning strategies. This multi-perspective approach will help to bridge the gap between top-down expert evaluation and bottom-up user needs, particularly in the context of human-centered deployment of SAVs in historic districts.

One limitation of the current study is that it employs a single weighting scheme (based on AHP–EWM) for aggregating expert evaluations. However, the existing literature suggests that stakeholder-based weighting strategies (such as equal weighting, experience-based weighting, and familiarity-based weighting) may influence final rankings of spatial indicators. Future research should incorporate a structured sensitivity analysis using these alternative schemes to examine the robustness and consistency of results. This would provide deeper insight into which indicators are most influential under varying decision-making assumptions.

4.2. Urban Space Optimization Strategies for Suzhou Old Town Based on AHP–EWM Analysis

This study conducted density analyses of relevant urban spatial elements (POI) in Suzhou old town and explored the potential impact of SAVs on the urban spatial pattern. Based on the AHP–EWM weighting results, this section discusses urban space optimization strategies along four key dimensions: transportation system optimization, public service reconfiguration, spatial equity enhancement, and cultural sensitivity management.

As shown in Figure 11a–c, the density distribution of bus stops, subway stations, and shared bicycle stations reveals abundant public transportation resources in Suzhou old town but insufficient subway coverage. The introduction of SAVs is expected to break the current reliance on fixed routes and stations, as their point-to-point operational mode can effectively fill gaps in the traditional transport system, enhancing accessibility and travel efficiency within the Old Town. Moreover, SAVs can offer alternative travel options for residents with significant freight or goods transport needs beyond private driving.

However, such optimization requires high spatial adaptability of Suzhou old town's morphology to SAVs. Issues such as narrow road widths and insufficient turning radii limit SAVs operational efficiency. Therefore, it is necessary to establish conveniently located SAVs PUDO points near existing high-density transport nodes and carry out micro-updates to surrounding spatial structures and residential environments. This approach will facilitate the transition from traditional node based transit to a flexible, surface based, and schedulable transportation network.

Figure 11d–f illustrate the clustered distribution of educational facilities, living service spaces, and public healthcare services, with resource concentration in the central southern area and sparse service density at the periphery. The temporal and spatial flexibility of SAVs can effectively compensate for these uneven distributions, particularly in off-peak periods, providing mobility support for vulnerable groups such as the elderly in accessing medical and daily services.

Priority should be given to incorporating residential areas with low POI densities related to living functions into the SAVs service coverage. Concurrently, the traditional concept of "facility radius" should be redefined—not based on conventional walking distances but integrating SAVs average response times, dispatch frequencies, and user preferences to construct dynamic accessibility models that enable spatial redistribution of public service facilities.

Figure 11h,i reveal a spatial mismatch between residential density and green space distribution, with green resources relatively lacking in high-density residential zones. The adoption of SAVs technology presents opportunities to reconstruct the coupling between living and ecological environments. On one hand, reducing private vehicle parking demands can free substantial ground space for the insertion of small scale green areas; on the other hand, SAVs dispatch systems can encourage residents to visit ecologically superior but more distant recreational sites, alleviating pressure on local green spaces.

Urban spatial planning should follow this bidirectional adaptation logic. SAVs integration can enable the redevelopment of released parking spaces into pocket parks, expanding urban green coverage. Simultaneously, green spaces should be incorporated into SAVs route planning to guide residents toward eco-friendly travel, thus supporting the ecological reorganization of Old Town at the policy level.

Figure 11g indicates that historic and cultural spaces are densely concentrated in the central and eastern parts of Old Town, reinforcing the spatial identity of Old Town as a "cultural core area." Nevertheless, SAVs deployment may pose potential physical and perceptual disturbances to historic districts. Sensitive management of SAVs operation routes and stopping nodes within these areas is required. Measures such as restricting SAVs operating hours or implementing mixed traffic modes combining slow moving vehicles with SAVs can preserve the spatial integrity of cultural spaces and maintain residents' travel quality.

From a spatial perception perspective, SAVs can also enhance the accessibility of cultural spaces, assisting visitors in quickly identifying cultural nodes and increasing the utilization of cultural resources [42]. Urban design strategies should establish transport nodes compatible with the old town's historic urban fabric at the edges of cultural districts, employing refined designs that integrate traffic behavior with spatial experience.

The spatial mismatch of green space resources is not only an ecological issue but also a manifestation of environmental inequality. In high-density residential areas lacking green space, the introduction of SAVs can help break spatial barriers to green access. On one hand, by reducing the need for parking, SAVs can free up ground-level space that may be converted into pocket parks or streetside greenery, thereby physically increasing green space supply (Figure 12). On the other hand, SAVs can enhance accessibility to peripheral large-scale ecological areas, easing pressure on central green spaces and promoting equal opportunities for ecological resource access. This approach aligns closely with the right to green access emphasized in the current environmental justice literature and resonates with the concept of spatialized justice [43]. Thus, green-oriented SAVs scheduling strategies are not merely about operational efficiency, but can also serve as governance tools to advance ecological justice and improve quality of life.

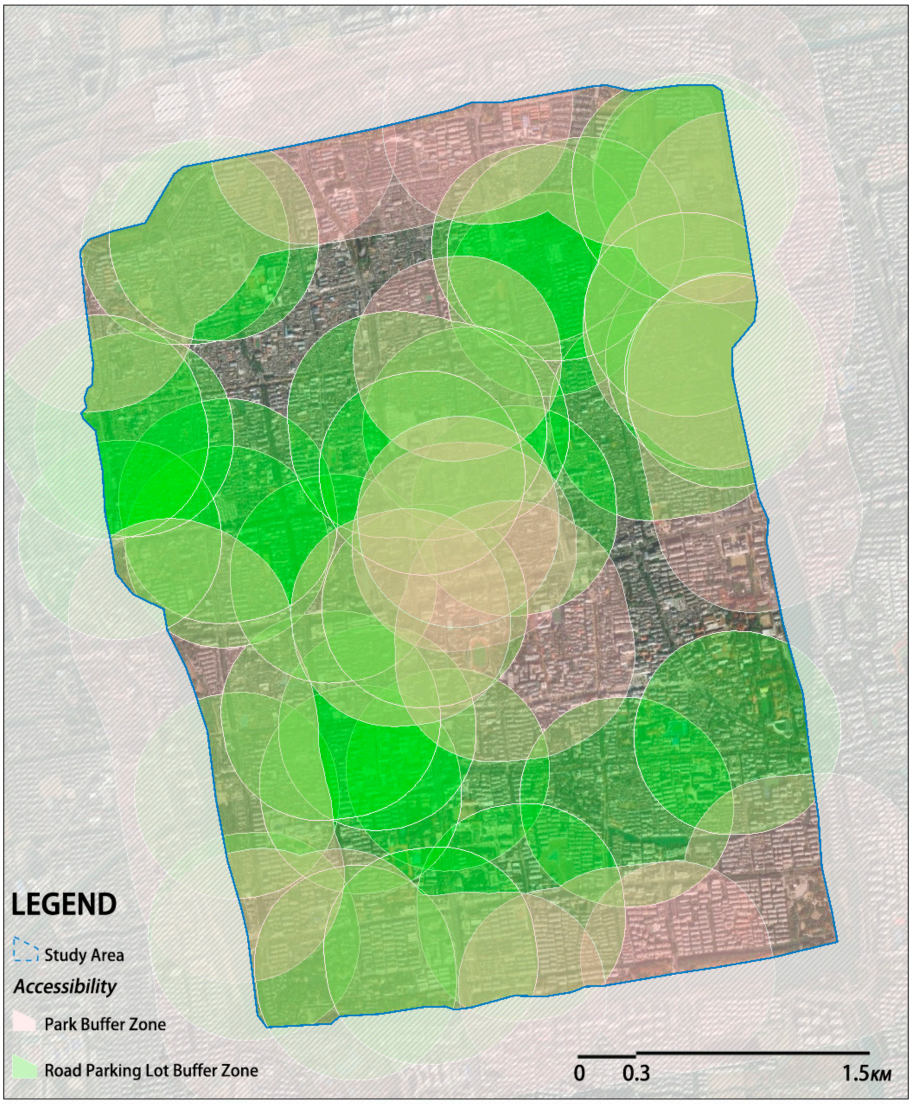

Figure 12. Releasing parking space can increase the coverage of urban green spaces (take the 500 m residential walking distance as a reference).

While this study provides a POI-based spatial density assessment, the current spatial analysis remains primarily descriptive. Although high-weight indicators such as healthcare accessibility or transit proximity have been mapped, further analytical integration between these weights and spatial mismatches remains a limitation.

Future research should apply spatial accessibility indices, buffer analysis, and weighted spatial overlays to link indicator weightings with actual gaps in service or coverage. Such spatial decision-support tools would facilitate more precise SAVs deployment strategies, including optimal stop placements, walkability zones, and prioritization of infrastructure upgrades.

The current study positions Suzhou old town as a representative case of dense, historic urban cores in East Asia. However, future research should further validate this generalization by employing a comparative urban typology framework. This may involve benchmarking spatial metrics such as density, road width, or service accessibility across historic centers like Kyoto, Seoul, to assess the degree of spatial similarity and enhance the transferability of the proposed strategies.

While this study is rooted in the specific context of Suzhou old town, its findings carry broader implications for historic urban areas globally. Many heritage cities—particularly in East Asia, Europe, and the Middle East—face similar spatial constraints, including narrow street patterns, aging infrastructure, and the need to balance modernization with cultural preservation. The proposed framework for evaluating SAVs readiness and spatial adaptability through integrated multi-criteria analysis and POI-based spatial diagnostics can be adapted to other historic cores with comparable morphological and functional characteristics. For instance, old towns in Kyoto, Istanbul, or Florence share a similar challenge in integrating emerging mobility technologies without compromising urban heritage. Thus, this study offers not only localized insights for Suzhou old town but also contributes a transferable planning approach for global cities navigating the transition toward intelligent, human-centered mobility in historically significant urban fabrics.

While this study focuses on Suzhou old town, the spatial challenges identified (such as limited street widths, unbalanced public service distribution, and green space mismatch) are common among many historic urban cores worldwide. Comparative reflections from cities such as Barcelona's Gothic Quarter, Istanbul's Fatih district, and Kyoto's Gion area demonstrate that the integration of SAVs in these complex urban fabrics poses similar dilemmas and opportunities. Kyoto, like Suzhou, faces the tension between conserving traditional streetscapes and adapting to modern mobility needs. Here, the limited availability of land and strong cultural preservation policies mean SAVs deployment must be aligned with historical sensitivity and minimal visual disruption.

These global comparisons reveal that the spatial logic of historic cities (shaped by centuries of organic development) is often at odds with modern mobility paradigms. The Suzhou case provides a valuable model for how SAVs can be spatially optimized in a heritage-sensitive manner while promoting spatial justice, environmental sustainability, and social inclusivity. Cross-contextual insights can help establish a broader planning framework where SAVs technologies are not simply imposed, but contextually adapted to support the evolving roles of historic cities in the 21st century.

4.3. The Trade-Off Between SAVs Infrastructure and Heritage Protection

While the deployment of SAVs systems can enhance accessibility, alleviate traffic congestion, and promote sustainable mobility in historic city centers, it also introduces tensions with heritage conservation objectives, particularly in culturally sensitive areas. Suzhou old town is characterized by a dense concentration of historical assets and a complex network of traditional alleys, often governed by strict spatial and regulatory constraints. The integration of SAVs may require modifications such as road widening, the installation of PUDO points, or the deployment of digital sensing infrastructure (e.g., sensors, navigational markers), all of which risk disrupting the physical fabric, visual landscape, and historical character of these traditional neighborhoods.

However, heritage protection should not be viewed solely as an impediment to SAVs implementation; rather, it can serve as a catalyst for innovation. Elements such as the spatial scale of alleys, pedestrian-oriented axes, and sightlines can be incorporated into SAVs route planning and speed control strategies, facilitating a synthesis between technology and cultural context. Such an approach not only preserves collective urban memory but also endows future mobility systems with spatial richness and historical depth, aligning with the cultural accessibility and identity dimensions emphasized in spatial justice theory.

Therefore, the deployment of SAVs systems in historic districts necessitates a cross-sectoral governance framework that brings together urban mobility planners, heritage conservation experts, and technology developers. Through collaborative development of context-sensitive regulatory guidelines and spatial intervention prototypes, it is possible to strike a dynamic balance between innovation and preservation.

5. Conclusions

This study, employing a combined AHP–EWM weighting approach, systematically analyzed the spatial distribution characteristics of SAVs related urban elements in Suzhou old town and explored the potential impacts of SAVs on the local spatial structure and resident needs. The results indicate that accessibility to transportation hubs holds the highest weight in expert assessments, highlighting it as a critical determinant of travel quality and urban operational efficiency. This reflects the imperative that, in dense historical environments like Old Town, SAVs systems should prioritize seamless connectivity to major transport nodes.

While Suzhou old town exhibits a generally balanced distribution of bus and shared bicycle stations, its limited subway coverage restricts overall accessibility. SAVs, with their point-to-point mobility advantages, offer the potential to fill critical gaps in the conventional transport network, especially in peripheral and underserved areas. However, realizing this potential hinges on spatial adaptability, particularly the redesign of narrow historic streets and the strategic placement of SAVs PUDO points.

Moreover, this study reveals a spatial mismatch between clustered public services—such as education, healthcare, and daily amenities—and low-density peripheral zones. The temporal and spatial flexibility of SAVs can serve as a compensatory mechanism, especially for vulnerable groups such as the elderly. Additionally, the observed disconnect between residential density and green space availability can be addressed through SAVs induced reductions in private parking demand, enabling micro-scale green infrastructure implantation and promoting green mobility pathways.

In areas rich in historical and cultural heritage, this study underscores the need for sensitive management of SAVs routing and stationing. While safeguarding spatial integrity and resident experience, SAVs can also enhance cultural accessibility and support the visibility and vitality of urban identity.

From the perspectives of spatial and environmental justice, the proposed optimization strategies reveal that the deployment of SAVs holds significant potential for reshaping urban spatial equity. In terms of public service provision, the high flexibility and dispatchability of SAVs can help dismantle the traditional facility-centric concentration patterns in historic city centers, thereby improving the everyday accessibility of marginalized populations and promoting a shift from spatial equality to functional equity. Regarding ecological resource utilization, SAVs can facilitate the reconstruction of urban ecological networks, enabling a transition from localized green spaces to regionally shared environmental assets, responding to the growing demand for high-quality environments among urban residents. This logic is not only applicable to Suzhou old town but also offers practical insights and theoretical references for historic urban districts worldwide striving to balance urban revitalization with spatial justice.

This research proposes a multidimensional urban renewal strategy that balances technological innovation with historical preservation, spatial optimization with user-centered needs. It offers both theoretical and practical guidance for the sustainable transformation of Old Towns under the influence of autonomous mobility. Nevertheless, it acknowledges that SAVs are not a panacea for all spatial challenges. The realization of their full potential depends on a deep integration with urban context, spatial logics, and socio cultural demands. The future of Old Town renewal lies not in resisting technological shifts, but in smart spatial guidance, regulatory alignment, and coordinated evolution between urban form and intelligent systems.

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Abbreviations

The following abbreviations are used in this manuscript:

AVs	Autonomous vehicles
AHP	Analytic hierarchy process
EWM	Entropy weight method
POI	Point of interest
PUDO	Pick-up/drop-off
RS	Remote sense
SAVs	Shared autonomous vehicles

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