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Leveraging Multi-Source Data for the Trustworthy Evaluation of the Vibrancy of Child-Friendly Cities: A Case Study of Tianjin, China

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Abstract: The vitality of a city is shaped by its social structure, environmental quality, and spatial form, with child-friendliness being an essential component of urban vitality. While there are numerous qualitative studies on the relationship between child-friendliness and various indicators of urban vitality, quantitative research remains relatively scarce, leading to a lack of sufficient objective and trustworthy data to guide urban planning and the development of child-friendly cities. This paper presents an analytical framework, using Heping District in Tianjin, China, as a case study. It defines four main indicators—social vitality, environmental vitality, spatial vitality, and urban scene perception—for a trustworthy and transparent quantitative evaluation. The study integrates multi-source data, including primary education (POI) data, street view image (SVI) data, spatiotemporal big data, normalized difference vegetation index (NDVI), and large visual language models (LVLMs) for the trustworthy analysis. These data are visualized using corresponding big data and weighted analysis methods, ensuring transparent and accurate assessments of the child-friendliness of urban blocks. This research introduces an innovative and trustworthy method for evaluating the child-friendliness of urban blocks, addressing gaps in the quantitative theory of child-friendliness in urban planning. It also provides a practical and reliable tool for urban planners, offering a solid theoretical foundation to create environments that better meet the needs of children in a trustworthy manner.

Keywords: child-friendly; urban analysis; urban vitality; multi-source data; vision large language models

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1. Introduction

The healthy growth of children is a key indicator of a society's level of civilization. As both the future of society and carriers of cultural heritage, children's well-being reflects a community's development level and humanitarian concerns. Therefore, fostering an environment that supports children's physical and mental development not only enhances their quality of life but also mirrors the overall progress of society [1].

Although urban centers often boast high-quality educational resources, the comprehensive development of children extends beyond academic achievements [2]. It includes access to nature, ample recreational spaces, life skills' cultivation, and mental health maintenance—essential factors in determining a city's child-friendliness [3]. The vibrancy of a city is evident in its bustling centers, with commercial districts and tourist attractions thriving during holidays [4]. Such environments offer children opportunities to engage in diverse social activities, interact with various cultural backgrounds, and develop a broader understanding of society and interpersonal skills.

Extensive research has explored the concept of urban vitality and its influencing factors, including spatial form, social structure, economic culture, demographic characteristics, and environmental quality [5]. While existing studies on child-friendly urban spaces are primarily qualitative, they establish a significant link between child-friendly environments and urban vitality. However, there is still a lack of research on their specific correlations. More focus is needed on the quantitative standards of child-friendly spaces and their impacts on urban vitality to better understand and enhance children's growth in urban settings. Urban planners must employ strategies that combine urban design, resource distribution, and public facility planning to create a multidimensional environment that nurtures the comprehensive development of children.

One effective method for conducting urban-scale analysis is through the utilization of Points of Interest (POI) data. POI data, which include information about specific locations such as businesses, parks, and cultural sites, can be crucial in understanding the distribution and accessibility of resources that contribute to urban vitality, particularly for children. Moreover, the recent advancements in deep learning have opened new avenues for urban perception through street view imagery. For example, some researchers employ semantic segmentation models [6] to analyze the green view index, which quantifies the visible vegetation in urban areas as seen from the street level. This type of analysis provides insights into the aesthetic and ecological aspects of urban environments, which are important for developing child-friendly spaces.

However, relying solely on predefined urban elements to gauge a city's character or vitality has its limitations, as this approach often results in static results that may not fully capture the dynamism and complexity of urban life. Recent advancements in Large Vision Language Models (LVLMs) [7–10] have addressed these limitations by offering powerful tools for obtaining detailed scene captions, which enhance the understanding of street views by describing them in rich detail [11,12]. This capability allows for a more nuanced and comprehensive analysis of urban spaces, revealing subtleties that traditional methods might overlook. Expanding on this idea, integrating LVLMs with Geographic Information Systems (GIS) and urban planning tools could revolutionize how cities are analyzed and planned [13].

In this paper, we present an analytical framework that integrates multi-source data, including POI counts, street view imagery, spatio-temporal big data, and captions from LVLMs, for the trustworthy evaluation of the vibrancy of child-friendly cities. This approach deepens the theoretical foundations of urban vitality research and provides essential insights into the internal functional layouts and spatial structures of cities, thereby enhancing thoughtful and effective urban planning. We also developed a weighted algorithm to amalgamate these diverse elements for comprehensive analysis. Utilizing Tianjin, China, as a testbed, our framework combines objective multi-source data with subjective field research to foster the development of vibrant, child-friendly neighborhoods in the city's aging central districts. Through such innovative methodologies, urban planners and researchers are better equipped to integrate child-friendly features into urban designs, creating environments that support the varied needs of children.

Our contributions can be summarized as follows: (1) a child-friendly evaluation system based on the vitality index was developed to quantify the child-friendly degree of urban blocks. (2) We utilized multi-source data to conduct trustworthy child-friendly urban analyses, incorporating an algorithm for weighted holistic assessments. (3) An evaluation of Heping District, Tianjin, China, confirmed the effectiveness of our methodology.

2. Related Works

2.1. Child-Friendly City

The concept of a Child-Friendly City (CFC) [1] originated from the 1989 United Nations Convention on the Rights of the Child, which promoted a rights-based approach to creating child-friendly environments. This led to key UN initiatives, such as UNICEF's Child-Friendly Cities Initiative. In 1996, UNICEF and UN-Habitat officially introduced the CFC concept at the Second United Nations Conference on Human Settlements in Istanbul. By 2009, UNICEF further defined CFCs [2], emphasizing the need to incorporate children's needs, potential, and rights into local policies, laws, platforms, and funding, viewing children as active decision-makers.

The CFC concept is not a fixed ideal but a framework designed to help cities become more child-friendly in areas like the environment, governance, and services. Brown highlights that the goal is to assist any city in improving child-friendliness across these dimensions. High-income countries, such as Sweden, Canada, and Lebanon, have actively embraced this initiative, prioritizing urban redevelopment to meet children's needs, focusing on areas like recreation, green spaces, traffic control, and road safety. However, Riggio notes that for many city governments, addressing children's issues remains a new challenge, requiring more exploration and innovation in policy development and implementation [14].

Research on child-friendly cities has made progress but remains in its early stages compared to other urban development studies. It focuses on four key areas: greening, public spaces, children's independent mobility (CIM), and children's participation in urban planning. Urban Green Spaces (UGS) [1,15] provide multiple benefits, such as reducing stress, improving mental health, and enhancing social cohesion, especially in disadvantaged communities. Ensuring access to green spaces is crucial for children's healthy development. Children's independent mobility is vital for their physical health, social skills, and autonomy [16]. Modern urban design often limits this by prioritizing motor vehicles over safe pedestrian and cycling environments. Addressing this need in urban planning is essential for creating child-friendly cities. Children should be active participants in urban planning, not just service recipients. Their involvement helps create sustainable, child-friendly communities. Encouraging children's autonomy and self-reliance through safe and challenging environments is key to their development [17–19].

2.2. Application of Multi-Source Urban Data in Evaluating Child-Friendly City

Current research on the application of multi-source urban data in evaluating child-friendly cities is still limited. However, some researchers have begun exploring the use of multi-source data to assess urban health and livability, offering new approaches and tools for evaluating child-friendly cities. Tomaras et al. [20] proposed a theoretical and practical approach that considers both air pollution and traffic congestion to estimate urban health. They developed the "HELIoS" (HEalthy Living Smart) framework, which integrates urban traffic and pollution data to diagnose the health of urban areas in smart cities. Although not specifically aimed at evaluating child-friendly cities, this method provides a model for using multi-source data in urban health assessment, which can be referenced for evaluating child-friendly cities [21].

Xing et al. [22] conducted a study on the accessibility and equity of high-density urban health resources based on multi-source big data. They developed a comprehensive framework, including Global Collaboration Location Quotient (GCLQ), Gaussian Two-Step Floating Catchment Area (2SFCA), and Gini coefficient, to evaluate the proximity, complementarity, accessibility, and equity of multi-level health resources in Guangzhou. This approach offers new insights for assessing the accessibility of children's health resources. Song et al. [23] used multi-source big data to dynamically assess population exposure to urban green spaces. They proposed a dynamic method that integrates Mobile Phone Location (MPL) data and high-resolution remote sensing images to more accurately assess residents', especially children's, actual exposure to urban green spaces, providing important references for planning child-friendly cities. Liu et al. [24] developed an urban livability assessment index system for Hong Kong, utilizing various datasets including statistical, geographic, and social media data. They extracted personal emotions from Instagram to measure urban livability and explored the relationship between personal emotions and urban livability. This innovative approach offers a new perspective for assessing children's emotional experiences in urban environments, helping to better understand children's perceptions and needs in cities.

Chen et al. [25] combined multi-source heterogeneous data to provide a basic evaluation framework for urban vitality and its driving forces based on the "5D" (Design, Diversity, Density, Distance, Destination Accessibility) theory. Although not specifically targeted at children, their methods and framework can offer valuable references for evaluating the vitality and livability of child-friendly cities.

2.3. Image Captioning

Starting with the CLIP [26] model, it achieved an alignment of visual and textual modalities through contrastive learning on a large number of image–text pairs. A series of works [7,27,28] improved upon CLIP by adopting strategies for more diversified data, effectively enhancing basic visual caption tasks [29–32]. BLIP [7] utilizes a bidirectional interactive encoder and effectively leverages noisy data from the web with synthetic captioning and filtering mechanisms, enabling the enhanced decoder to generate richer and more accurate image descriptions. BLIP-2 [27] incorporates a transformer called Q-Former, designed to bridge the gap between a frozen image encoder and large language models (LLMs), offering computational efficiency and exceptional performance across various vision–language tasks, including image captioning. The LLaVA [8] model focuses on instruction-based fine-tuning to enhance its application in multimodal scenarios, emphasizing joint fine-tuning of the language model and projection layers while keeping the weights of the vision encoder fixed. It demonstrates strong command-following performance.

As models improve, the importance of data quality and expanding data domains also becomes increasingly significant. For instance, LLaVA employs plain text GPT-4 [33] to generate visual language instructions directly from COCO annotations, marking the first attempt to extend instruction tuning to a multimodal language–image space. This approach not only enhances the model's zero-shot capabilities for new tasks but also improves its handling of complex visual understanding tasks, demonstrating the importance of effective training with high-quality data. Following this, with the more powerful GPT-4-Vision (https://www.openai.com/, accessed on 12 July 2024), the ShareGPT4V [9] dataset was created through a meticulously designed data collection and generation process, including high-quality image–text pairs. These descriptions cover a broad range of world knowledge and object attributes, as well as multidimensional information such as spatial relationships and aesthetic evaluations. The descriptions in the dataset have an average length of 942 characters, significantly longer than those in traditional datasets. Using this dataset, the ShareGPT4V-7B model performed optimally in 9 out of 11 multimodal benchmark tests, further proving the critical role of high-quality data in training such complex models.

3. Method

Although different scholars have various definitions and focal points regarding child-friendly urban spaces, there is a consensus that children need access to basic educational resources, safe and convenient travel routes, sufficient green ecological environments, child-oriented commercial and social spaces, and ample play and activity areas. As illustrated in Figure 1, we present the complete pipeline for our urban child-friendly analysis. First, key indicators are defined and calculated using appropriate methods. These indicators are then integrated through a weighted holistic assessment to generate a child-friendly density map for the entire urban area. The analysis is implemented in Heping District, Tianjin, China. The study area is shown in Figure 2. Heping District is the smallest of the six main urban districts in Tianjin, with a total area of 9.98 square kilometers and a registered population of 476,300. It has many high-quality primary and secondary schools, and many parents are proud of their children's registered residence in Heping District. According to the Statistical Bulletin of the National Economic and Social Development of Heping District in 2023, there are 43,189 primary school students and 32,191 ordinary secondary school students in the district, including 19,695 junior high school students and 12,496 high school students.

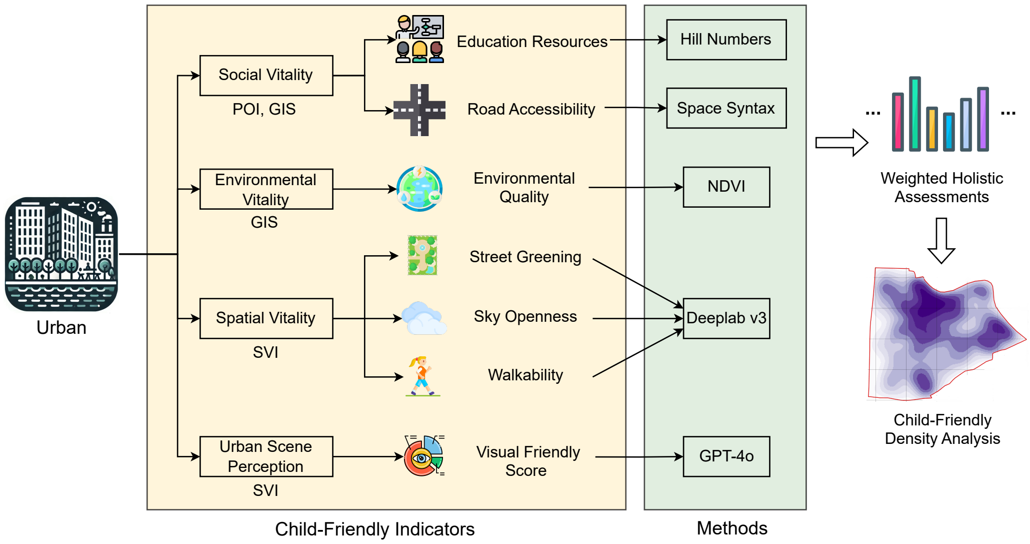
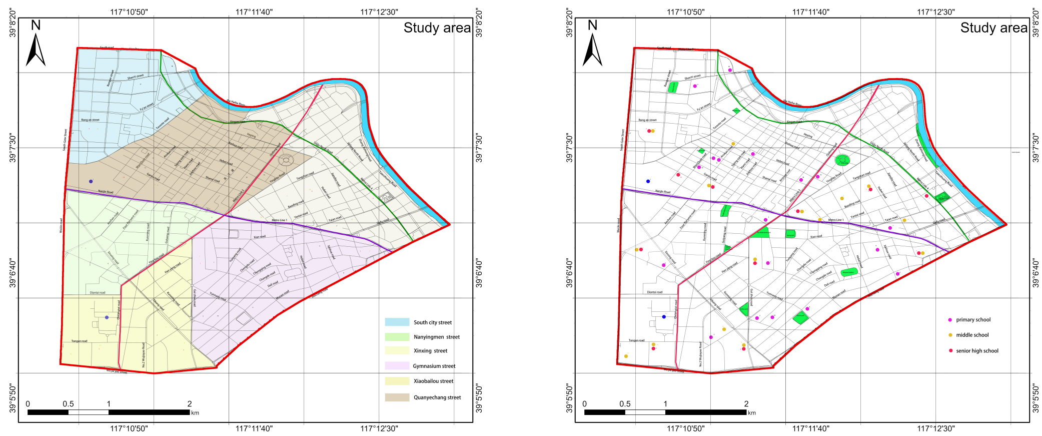


Figure 1. Pipeline for our urban child-friendly analysis. Key indicators are defined, calculated, and integrated into a weighted assessment, resulting in a child-friendly density map for the urban area.



(**a**) Administrative Division Map (**b**) School and Park Distribution Map

Figure 2. Studyarea of Heping District, Tianjin, China. Light Blue—South city street; Light Green—Nanyingmen street; Light Yellow—Xinxing street; Light Purple—Gymnasium street; Light Pinkish Yellow—Xiaobailou street; Beige—Quanyechang street. Purple dots represent primary schools, yellow dots represent middle schools, and red dots represent senior high schools.

3.1. Child-Friendly Space Activity Indicators

Referring to previous works [1,15], we defined the following four main indicators for quantitative evaluation: social vitality, environmental vitality, spatial vitality, and urban scene perception. In the following sections, the details are provided.

3.1.1. Social Vitality

Social vitality I_{so} is important in building a child-friendly urban environment. A community with strong social vitality usually has high residential participation and provides a safe and interactive growth environment for children, where they can play and explore freely [34]. In addition, vibrant communities can provide rich and diverse cultural, educational, and recreational activities, which are important factors in promoting the all-round development of children. Such communities can also attract more educational resources, such as high-quality schools and interest classes, which help improve children's academic and social abilities.

We used POI data for this calculation. They were obtained from Amap API, and the collection time was June 2023. A total of 286 pieces of POI information related to this study were obtained from kindergartens, primary schools, middle schools, and cultural palaces. And then, the Hill Numbers method was utilized to calculate the richness as follows:

$$^{q}D = \left(\sum_{i=1}^{S} p_i^q \right)^{\frac{1}{1-q}}, \tag{1}$$

where ^{q}D is a measure of diversity expressed as the "effective number of types of diversity". S is the total number of types of educational facilities, and p_i is the proportion of educational facilities of the i-th type in the total number of facilities. The parameter q is a non-negative real number that determines how diversity is measured. We use $q = 1$, where the relative frequencies of all types are taken into account, and this value can be used to measure the richness and balance of educational facilities. This is the most commonly used diversity measure because it balances the number of types and the uniformity of the types. When $q = 1$, the Shannon index takes into account not only the number of species in a community (richness), but also the proportion of individuals of each species (evenness), which enables it to more comprehensively reflect the complexity and stability of a community [35].

To calculate road accessibility, we first obtained road networks and other relevant spatial elements from ArcGIS and used a space syntax toolkit to convert map data into a topological network. This network was constructed based on the connectivity of roads or paths. Next, we evaluated this indicator from two aspects: (1) integration is an indicator that measures the accessibility of a point in the network. A high integration area indicates that the average distance from this point to all other points is shorter, which represents higher accessibility. (2) Connectivity is a measure of how many other nodes a node is directly connected to. It reflects the direct reachability of a point in a local network. High connectivity means that a node or location is directly connected to multiple other nodes, making it potentially easier to reach and leave. Both calculations were performed using ArcGIS 10.5 (Esri, Redlands, California, USA).

Finally, we used the average to combine these two aspects as follows:

$$I_{so} = \frac{I_{edu} + I_{road}}{2}, \tag{2}$$

where I_{edu} and I_{road} are values for basic education resources and road accessibility, respectively.

3.1.2. Environmental Vitality

Environmental vitality (I_{en}) plays a key role in building child-friendly cities. It involves the quality, sustainability, and ecological health of the natural environment, providing safe and inspiring spaces for children. A city with high environmental vitality will have plenty of green spaces and parks, ensuring that children can safely engage in outdoor activities, which is essential for their physical health and emotional development. In addition, good air and water quality are particularly important for the healthy development of children, as they are more sensitive to environmental pollution.

We calculated the Normalized Difference Vegetation Index (NDVI) for this indicator. The calculation is performed as follows:

$$\mathrm{NDVI} = \frac{(NIR - RED)}{(NIR + RED)}, \tag{3}$$

where NIR stands for the reflectance value of the near-infrared band, while RED stands for the reflectance value of the red band. This formula evaluates the health and coverage of vegetation by comparing the difference between the two bands. We used ArcGIS for the calculation of this indicator.

3.1.3. Spatial Vitality

Spatial vitality (I_{sp}) refers to the energy and attractiveness of an area and is generally related to the frequency and diversity of activities in the area, as well as spatial features that promote interaction among people. Spatial liveliness is particularly important for child-friendly environments because it affects children's physical activity, social interaction, and psychological well-being. We analyzed this indicator from three aspects using the semantic segmentation model Deeplab v3 [36] (trained with CityScapes dataset [37]) and Street View Images (SVIs) from Baidu Map. As shown in Figure 3, there were a total of 18,703 data points (denote as collection $\mathcal{D}$) with corresponding panorama obtained for this indicator.

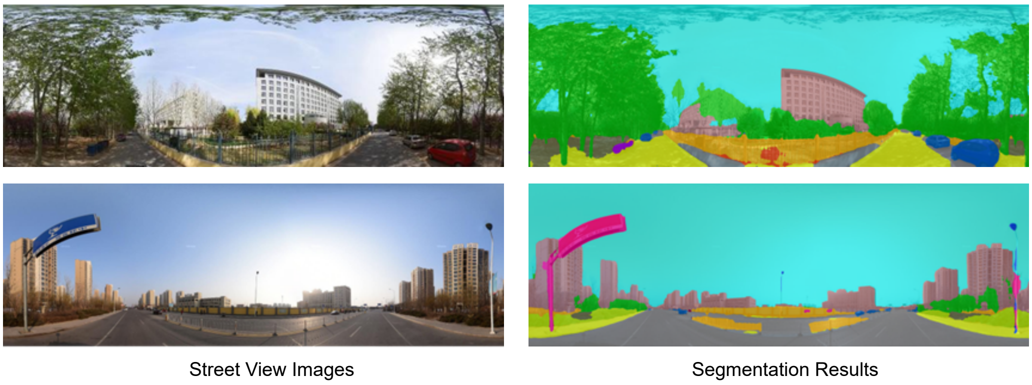


Figure 3. Samples of semantic segmentation via Deeplab v3.

Street greening beautifies the urban environment by adding natural elements such as trees, shrubs, and gardens, which not only improve the beauty and comfort of the city but also provide children with opportunities to contact and explore nature. We calculated the Green View Index (GVI) for each SVI as follows:

$$GVI = \frac{Area_{green}}{Area_{all}}, \tag{4}$$

where $Area_{green}$ is the number of green pixels, and $Area_{all}$ is the total number of pixels in the image.

Sky openness refers to the extent of sky that can be seen in an urban environment, which is important in creating a feeling of openness and spaciousness. It can reduce feelings of depression and promote mental health. Similar to (4), we calculated the ratio of sky pixels on the image.

A walkable urban environment means people can walk to their destinations safely and easily. For children, it can increase physical activity, independent ability, and social interaction. Similar to (4), we calculated the ratio of sidewalk pixels in the image.

Spatial vitality is very important for a child-friendly environment, as it affects children's physical activity, social interaction, and mental health. For the overall evaluation of this indicator, we normalized the value for each aspect and summarized them together for each data point.

3.1.4. Urban Scene Perception

The urban scene perception I_{per} of SVIs is important for identifying child-friendly urban environments. Compared with the pixel statistics of semantic segmentation, the text description of perception can restore the scene in SVI more specifically. This perception helps people understand and evaluate which elements of urban design are particularly friendly to children, such as spacious sidewalks, safe crossing facilities, ample green space, and play facilities. By identifying and enhancing these elements, we can better design and transform urban spaces to make them more suitable for children's growth and activities, thereby improving the quality of urban life for children.

To illustrate this, Figure 4 presents an example of the implementation of our child-friendly scoring method. We first employed an LVLM Phi-3V [38] to realize the image caption process from an SVI to a scene text description (using the prompt "Describe all the visual information of the input panoramic street view image"). It was implemented for each data point. Subsequently, we used GPT-4 o [33] to score the child-friendly level of the textual descriptions. This method allows us to quantitatively evaluate how child-friendly an urban scene is based on textual analytics, providing a scalable approach to assessing and improving urban spaces from a child-centric perspective. As shown in Table 1, we demonstrate the criteria for scoring (the points range from 1 to 5), which are used as the prompt for scoring.

Table 1. Criteria for scoring child-friendly level for text description of an SVI.

Points	Criteria
1	The street scene described has almost no child-friendly features. The scene mentions obvious safety hazards, such as traffic congestion, lack of sidewalks, or absence of clear safety signs. There are no suitable entertainment facilities or activity areas for children. The environment is noisy, unclean, and unsuitable for children to linger. There are no educational elements, and no consideration is given to the needs of children.
2	The street scene described has a few child-friendly elements, but overall, it is not attractive or suitable for children. The scene mentions some potential safety hazards without clear safety measures. There are very few entertainment facilities for children, and these facilities are not engaging. The environmental conditions are poor, making it possibly unsuitable for children to stay long. Educational elements are scarce and insignificant, with child-friendly elements limited to specific age groups.
3	The street scene described shows some degree of child-friendliness but has notable shortcomings. The scene includes some safety facilities, but safety hazards are also present. There are some suitable entertainment facilities or activity areas for children, but they are not highlighted in the description. The environment is average, with a few comfortable areas, but the overall impression is mediocre. The scene includes some basic educational elements, such as landmark buildings or museums, but these are not emphasized. The description mentions some child-friendly elements but does not cover them comprehensively.
4	The street scene described is generally very child-friendly, with only a few areas for improvement. The scene has good safety measures, such as clear traffic signs and safe crossing facilities. There are several engaging entertainment facilities for children that cater to different age groups. The environment is comfortable, with suitable rest areas and green spaces for children. The description includes clear educational elements, such as educational boards and interactive facilities. The street scene has good inclusivity, with multiple child-friendly facilities that are suitable for children of different ages.
5	The street scene described is highly suitable for children, covering all aspects of safety, entertainment, education, environmental comfort, and inclusivity. The description emphasizes a high level of safety, with special safety measures designed for children, such as slow traffic and child-specific areas. The street scene has rich entertainment facilities for children that spark their interest and offer various ways to play. The environment has a strong educational atmosphere, with several interactive and educational facilities that stimulate children's learning interest. The scene highlights environmental comfort, such as fresh air, a quiet atmosphere, and child-friendly green spaces and rest areas. The street scene has excellent inclusivity, fully considering the needs of children of different ages.

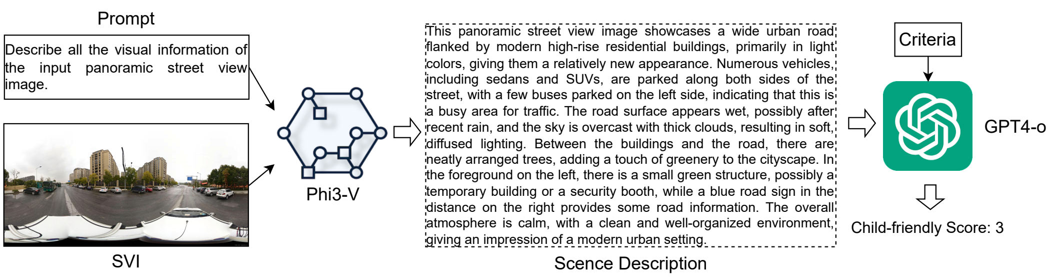


Figure 4. An example of a child-friendly perception pipeline.

3.2. Weighted Holistic Assessments

In the preceding sections, we quantified child-friendliness using various indicators. However, it is essential to conduct a comprehensive evaluation that integrates these indicators to gain a more holistic understanding of child-friendly environments. We, thus, adopt the entropy weight method for this purpose. This method allocates weights according to the variability of each indicator, with higher variability leading to a higher entropy and, consequently, a greater weight. An indicator with a greater weight has a greater effect on quantifying child-friendliness. We denote all the data points in the experimental area as $\mathcal{D} = \{d\}$. For one data point, there are four indicator values defined in the above sections as $I^d = \{I^d_{so}, I^d_{en}, I^d_{sp}, I^d_{per}\}$. Thus, all the data points can be represented as $X = (x_{ij})_{m\times n}$, where x_{ij} represents the value of the i-th sample at the j-th indicator. m and n are the number of data points and indicators. The standardized data matrix $Y = (y_{ij})_{m\times n}$ is calculated as follows:

$$y_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)}, \tag{5}$$

where $\min(x_j)$ and $\max(x_j)$ are the minimum and maximum values of the j-th indicator, respectively. Then, for each indicator j, we calculate the weight p_{ij} of the i-th sample on the indicator:

$$p_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}}. \tag{6}$$

The information entropy E_j is calculated as follows:

$$E_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} p_{ij} \ln(p_{ij}), \tag{7}$$

where m is the number of data points, ln is natural logarithm, and $p_{ij} \ln(p_{ij})$ is defined as 0 when $p_{ij} = 0$. The coefficient of variation d_j is calculated as $d_j = 1 - E_j$, and the final weight w_j of each indicator is calculated as follows:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j}. \tag{8}$$

Thus, the weighted child-friendly score is calculated as follows:

$$\bar{I}^d = w_1 \times I^d_{so} + w_2 \times I^d_{en} + w_3 \times I^d_{sp} + w_4 \times I^d_{per} \tag{9}$$

3.3. Experimental Settings

We collected the required POI data and street view images from Baidu Maps and utilized ArcGIS for data analysis and processing. Road networks and other relevant spatial elements were extracted from ArcGIS, and the Space Syntax Toolkit was applied to convert map data into a topological network. For semantic segmentation and the Phi-3V model implementation, we used the official code and environment, running the programs on an Nvidia A6000 GPU. Additionally, we employed OpenAI's API "gpt-4o" for automated scoring.

4. Visualization and Analysis

4.1. Social Vitality Analysis

4.1.1. Vitality via Basic Education Resources

As shown in Figure 5, we demonstrate the density of four different basic education resources through POI data. Firstly, kindergartens appear fairly distributed, indicating a uniform spread throughout the region, with notably higher concentrations in the central and northwestern sections. This suggests a broad reach, likely due to the widespread need for early childhood education facilities. In contrast, primary schools show a denser distribution with several pronounced high-density clusters, particularly in the middle and northeastern parts of the area. This could be a reflection of higher student populations and the essential nature of primary education, necessitating more schools to accommodate the demand. Middle schools display a more even distribution compared to primary schools, though still with significant clusters in the central and eastern areas. This might indicate fewer overall facilities but a targeted establishment where demographic and educational needs converge. Lastly, the cultural palaces exhibit very distinct, isolated high-density spots, starkly different from the more dispersed schooling facilities. These spots are scattered as individual points, suggesting that cultural palaces are less uniformly needed or possibly cater to specific cultural and community activities concentrated in certain areas.

This distribution might correlate with the specific functions and audience each type of educational institution serves. Kindergartens and primary schools, catering to a broad age range and large student bodies, have a widespread presence. In contrast, middle schools and cultural palaces, possibly due to their specialized nature or specific service demands, are more concentrated, reflecting strategic placement in response to local community needs.

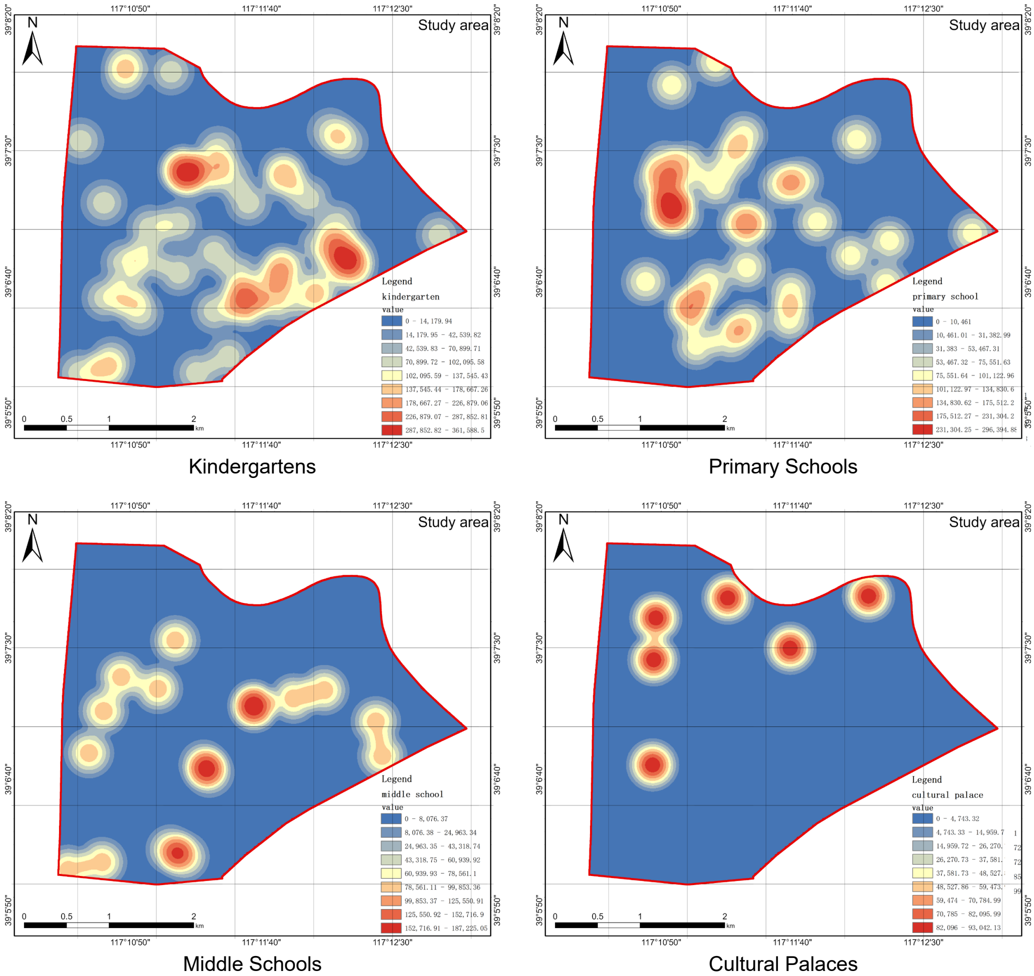


Figure 5. Density of social vitality for different basic education resources.

4.1.2. Vitality via Road Accessibility

Heping District in Tianjin is favored by parents for its numerous well-reputed primary and secondary schools. This study conducted a spatial syntax analysis of Heping District, an administrative region rich in basic educational resources, and we propose strategies to enhance the vitality of child-friendly urban neighborhood spaces in Tianjin. Based on pedestrian density data from Baidu Huiyan's space–time big data on 2 May, 13 April, and 18 April 2024, in Heping District, pedestrian density distribution maps during holidays, weekdays, and weekends were produced using ArcGIS 10.5 (Esri, Redlands, California, USA) software to analyze the vitality of child-friendly urban neighborhood spaces in Tianjin. It is generally believed that people prefer to walk when the travel radius is under 1200 m; therefore, we conducted a segment analysis on pedestrian areas in Heping District with walking distances of 250 m (2–3 min), 500 m (5–8 min), 800 m (10–12 min), and 1200 m (15–20 min).

Figure 6 shows in detail the relationship between the integration of urban areas and pedestrian flow density during peak hours in the morning and evening on weekdays through four different study ranges (R = 250 m to R = 1200 m). Areas with high integration (marked in yellow) are usually concentrated, indicating that these areas have higher accessibility and connectivity and tend to attract more pedestrian flow, especially during peak hours. As the study range expands, areas with a high integration gradually spread to cover wider areas, which reveals the key transportation nodes of the city. The distribution of pink and dark purple points reveals the differences in the geographical distribution of pedestrian flow during peak hours in the morning and evening, reflecting the commuting patterns between work and residential areas. We also show connectivity in Figure 7. Looking at different study ranges shows how connectivity spreads outward from the central area. Smaller ranges (such as R = 250 m and R = 500 m) may focus on the core area of the city, while larger ranges (such as R = 1200 m) provide a more comprehensive understanding of connectivity in the surrounding areas.

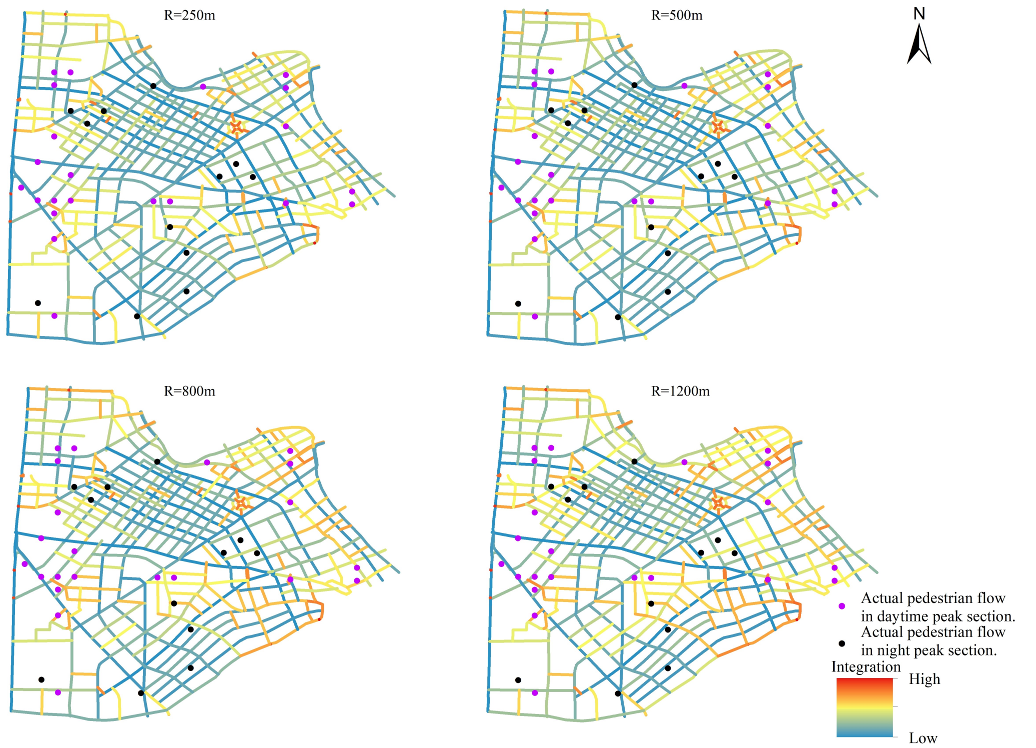


Figure 6. Comparison of integration degree and passenger flow density during morning and evening peak hours on weekdays.

4.2. Environmental Vitality Analysis

Figure 8 shows the distribution of the NDVI in the experimental area, with colors ranging from light green to dark green representing varying vegetation coverage. In the figure, areas with higher vegetation coverage are concentrated in the middle of the city, which may represent abundant green spaces and parks, while areas with lower coverage are distributed on the outskirts of the city, which may be areas with dense buildings or under development. For child-friendly cities, the accessibility and environmental quality of green spaces are crucial. The areas with a higher NDVI in the figure not only provide good outdoor activity spaces but also may mean better air quality and a more pleasant climate, suitable for children to live and play. However, the uneven distribution of vegetation also suggests that urban planning should focus on increasing green space coverage, especially in areas with a currently low NDVI, to ensure that all children have equal access to high-quality outdoor environments and green spaces, and to improve the overall livability and child-friendliness of the city.

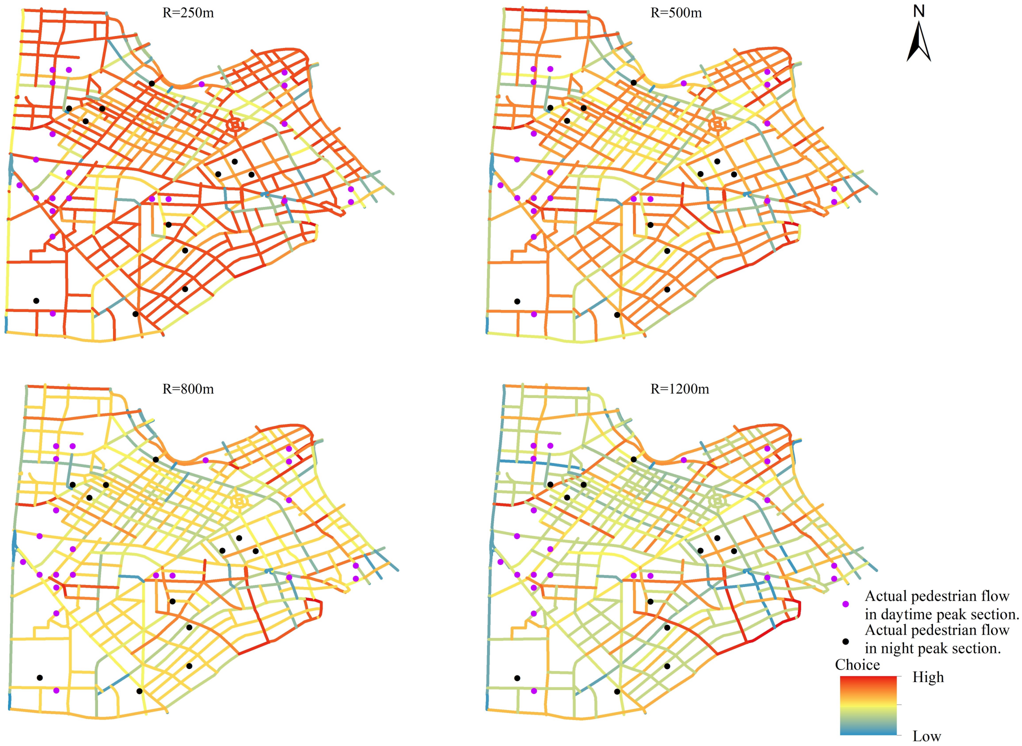


Figure 7. Comparison of connectivity degree and passenger flow density during morning and evening peak hours on weekdays.

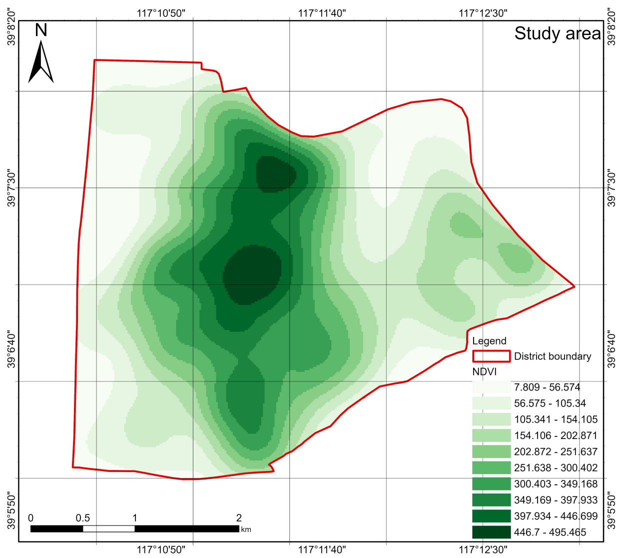


Figure 8. Visualization of NDVI analysis.

4.3. Spatial Vitality Analysis

As shown in Table 2, we display the proportion of pixels for each category across all SVI images. The overall green view index is calculated to be 5.9%. According to related studies, a green view index below 15% indicates a strong sense of artificial construction; between 15 and 25%, residents feel relatively relaxed while walking in road spaces; between 25 and 35%, green plants have the strongest effect in relieving residents' stress. In this project, the green view index in the basic education hub areas significantly fails to meet residents' needs for a green ecological lifestyle. In the centers where educational resources are concentrated, children's growth requires a good natural environment. A low green view index negatively affects both children and other residents psychologically and physiologically. The vehicle visibility rate is 1.3%, which only reflects the street conditions when there are fewer motor vehicles in the early morning. During the morning and evening rush hours, the vehicle visibility rate is higher as recorded by drone aerial photography.

Table 2. Average area distribution in the SVIs.

Number	Category	Percentage of Area in the Image (%)
1	Sky	62.5
2	Road	13.3
3	Sidewalk	1.5
4	Vehicles	1.3
5	Trees	4.7
6	Grass	0.5
7	Green Plants	0.7
8	Buildings	9.6
9	People	0.03
10	Land	0.9

The sky occupies a substantial 62.5% of the area in the image, which indicates a dominant visual presence of the sky. This high percentage could be a factor contributing to an open and less cluttered visual experience in the depicted scene, possibly enhancing feelings of openness and freedom for viewers or residents in the area. The sidewalk covers only 1.5% of the area in the image. This relatively small percentage suggests that the sidewalk space is limited, which might impact pedestrian movement and accessibility. Such a small proportion of sidewalk space in an urban environment might contribute to congestion and could be inadequate for high pedestrian traffic, potentially leading to a less comfortable and safe pedestrian environment.

We also visualize the overall distribution of vegetation (greening), sky, and sidewalk (walkability) in Figure 9. Vegetation is concentrated in the central area, especially in the north and south, indicating that these areas have more green space; in the west and east of the city, vegetation is more sparse. The sky view is more open in several areas in the northwest and east, especially in places with few or low buildings, where the sky can be seen more. The road network is relatively evenly distributed throughout the city but is particularly dense in the central and northern parts of the city, reflecting that these areas may be transportation hubs and important facilities.

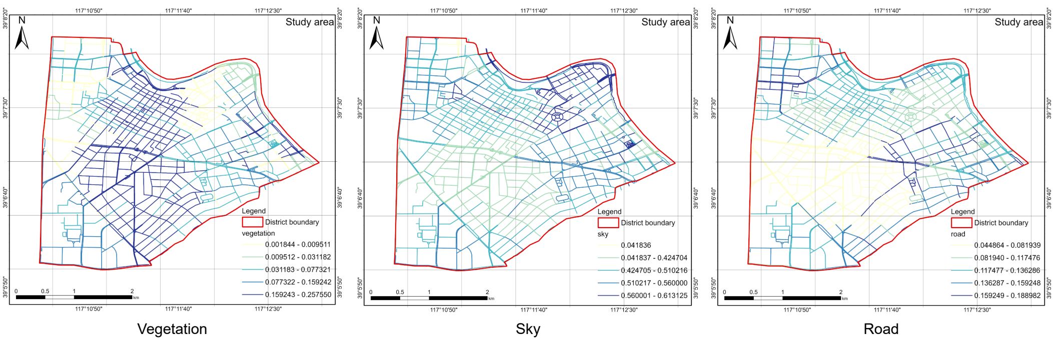


Figure 9. Visualization for vegetation (greening), sky, and sidewalk (walkability).

4.4. Urban Scene Perception Analysis

We implemented the above process for all SVIs in this study and visualize them in Figure 10. This image shows a grid of areas, with each grid assigned a visual friendliness score from 1 to 5, with different shades of blue indicating higher or lower scores. This score may be based on the surrounding environment, the child-friendliness of the facility, or other relevant criteria. The grid allows the observer to clearly see the score for each specific location. Overall, child-friendliness is higher in the center and north of the study area.

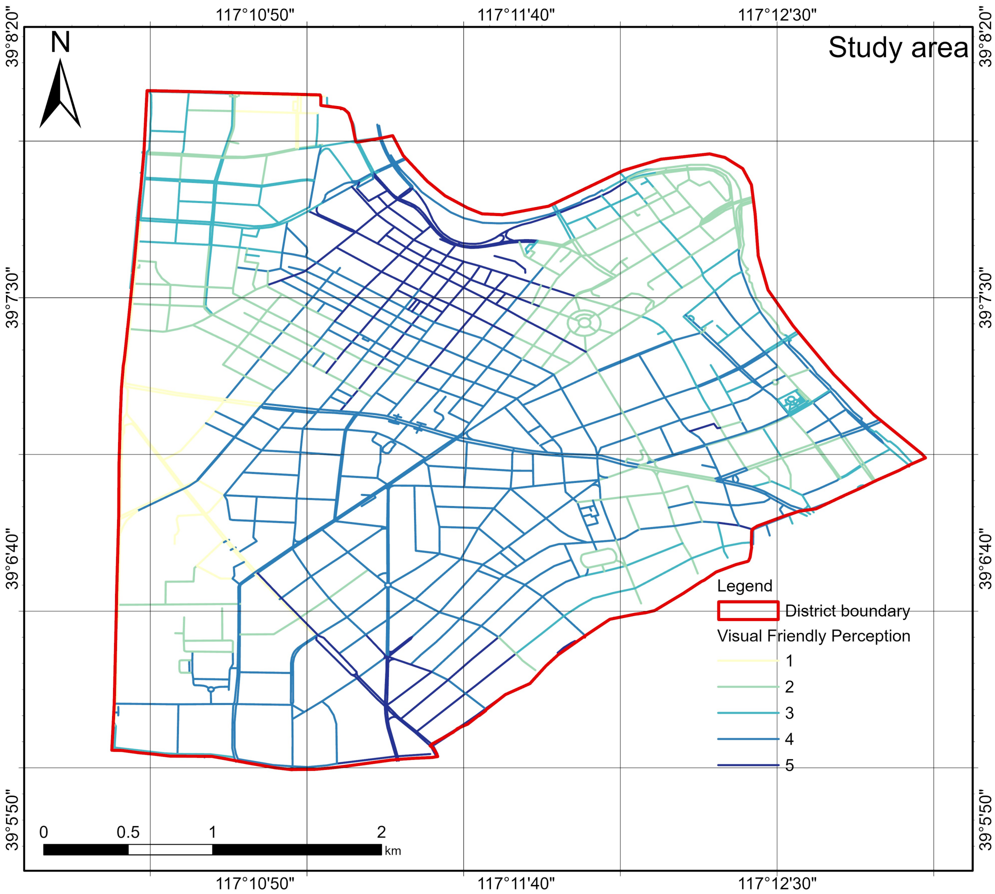


Figure 10. Child-friendly perception scoring visualization.

We also analyzed the frequency of the top 20 words in the captions of SVIs (Street View Images) with a child-friendly score exceeding 3. As shown in Figure 11, the histogram illustrates the distribution of these frequently occurring nouns. Notably, "Building" appears most frequently in these descriptions, with over 3500 occurrences. This suggests that, although these areas are considered child-friendly, they contain a significant number of buildings, possibly due to the safety these structures provide or the convenience of infrastructure. In addition, natural elements like "Tree" and "Park" also appear frequently, reflecting the importance of green spaces and outdoor activity areas in these child-friendly regions. On the other hand, "Bike" and "Car" are also common but occur less frequently than buildings and natural elements. This might indicate that these areas restrict motor vehicles to some extent, ensuring children's safety. Overall, these frequently occurring nouns offer a deeper understanding of the characteristics of child-friendly areas, highlighting the importance of safety, green spaces, and necessary infrastructure in these environments.

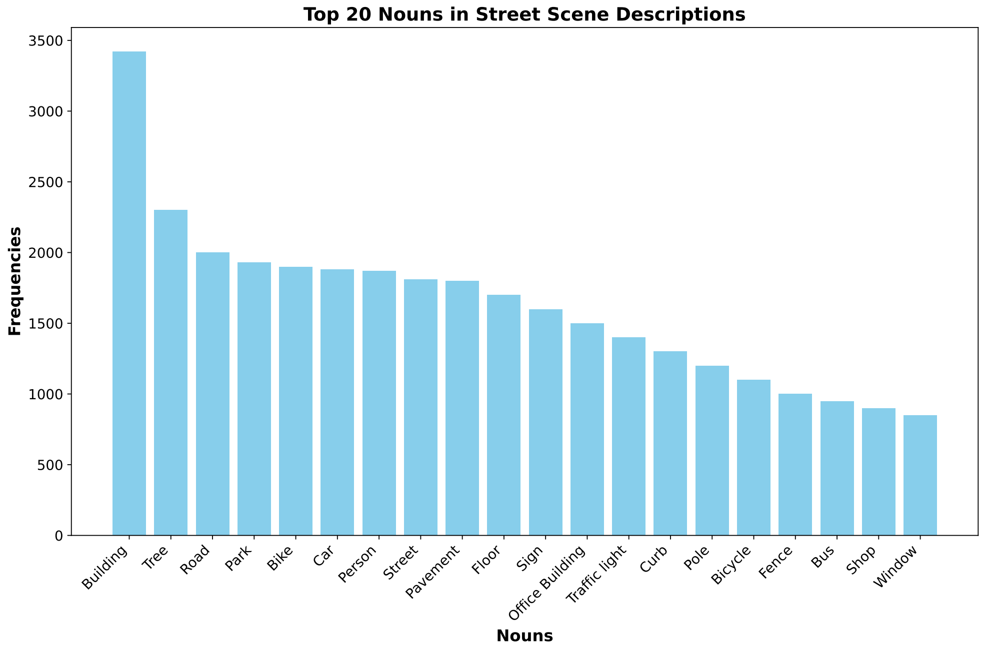


Figure 11. Frequency of nouns appearing in captions of SVIs labeled as child-friendly score exceeding 3.

4.5. Weighted Holistic Analysis

As introduced in Section 3.2, we used the entropy method to merge all indicators. Table 3 presents the weights of various indicators calculated using the entropy weighting method. Specifically, the weight for I_{per} is 0.226, indicating a relatively high importance in the analysis. In contrast, I_{en} has the lowest weight at 0.048, suggesting minimal impact on the overall evaluation. The weight for I_{sp} is moderate at 0.155. Notably, I_{so} has the highest weight at 0.571, making it the most significant indicator among all, greatly influencing the final outcome. The entropy weighting method assigns weights based on the variability of each indicator; indicators with greater variability have a higher entropy and a higher weight, which suggests I_{so} likely has the highest variability, hence the highest weight.

Table 3. Weight for each indicator using entropy weight method.

Indicators	I_{so}	I_{en}	I_{sp}	I_{per}
Weight	0.571	0.048	0.155	0.226

After summarizing the weight of all indicators, we visualize the child-friendly results in Figure 12. This heatmap displays the spatial distribution of child-friendliness perceptions within a study area. It is evident from the map that higher perceptions of child-friendliness are concentrated in the central and some peripheral areas, indicated by darker colors, suggesting these regions are more suitable for children to live and engage in activities. Conversely, other areas show lighter colors, denoting lower child-friendliness perceptions. This distribution may be related to the locations of local parks, schools, and other child-friendly facilities. Through this comprehensive weighted analysis, urban planners and policymakers can gain a clearer understanding of which areas perform well in terms of child-friendliness and which ones need improvement, allowing for more targeted decision-making and resource allocation.

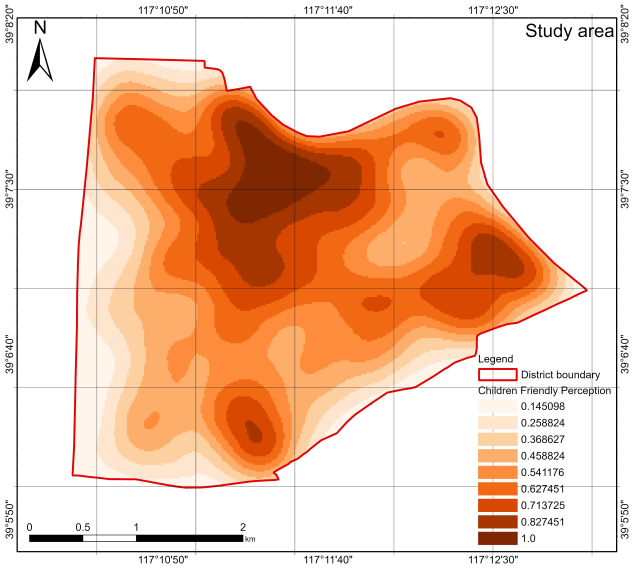


Figure 12. Visualization of weighted holistic analysis for child-friendly evaluation.

Based on the analysis of the charts, the area with the highest weighted score for child-friendliness in Heping District is the central region south of Nanjing Road. This area is home to several schools and parks, and Heping Road Commercial Street is also located here. Following this, the western part of Heping District near the Haihe River also scores high, featuring high-quality urban public spaces. Another area with a high weighted score for child-friendliness is the Five Avenues (Chongqing Road, Changde Road, Dali Road, Munnan Road, and Machang Road) cultural tourism zone. The analysis of Heping District reveals that this result aligns closely with subjective analysis, indicating that schools and cultural tourism spaces are key locations that naturally promote children's active participation. However, the environmental vitality score in Heping District is relatively low, suggesting that environmental factors have insufficient influence on the child-friendliness of the area. Combined with subjective judgments and the NDVI visualization in Figure 7, it can be concluded that Heping District generally has a low green view index, and further improvements are needed by integrating block-level conditions to create more concentrated and larger green spaces.

5. Discussion

5.1. Comprehensiveness of Child-Friendly Indicators

In our study, we established a set of child-friendly indicators that are crucial for assessing the child-friendliness of urban neighborhoods. These indicators encompass various aspects of urban life, such as educational resources, green spaces, and cultural facilities, aiming to comprehensively reflect the quality of life and developmental conditions for children in urban environments. By setting these indicators, we can better understand which factors are vital for the holistic development of children and provide scientific evidence for urban planners to optimize city designs, creating environments more conducive for children's well-being.

However, despite our efforts to cover multiple dimensions of child-friendliness, these indicators may still have certain limitations. The complexity of urban environments and the diverse needs of children mean that any set of indicators may not fully capture all the factors influencing children's well-being and development. For example, differences in cultural background, family structure, and the city's economic level could lead to varying interpretations and needs regarding child-friendliness. Therefore, future research could further expand and refine these indicators, especially by considering different socioeconomic and cultural contexts, to provide a more comprehensive reflection of a city's child-friendliness.

5.2. Quantification of Child-Friendly Urban Environments

To accurately assess the child-friendliness of urban areas, we employed multiple methods to quantify this friendliness. These methods include traditional statistical analysis and spatial data processing, as well as advanced deep learning techniques and image analysis tools, to capture various aspects of the urban environment comprehensively. Notably, we used the entropy weight method to integrate different indicators and derive an overall distribution of city-wide child-friendliness. This approach effectively addresses the complexity of multi-source data, helping to eliminate biases in subjective weight settings, thus making the evaluation results more objective and reliable.

Nevertheless, there is still room for improvement in this approach. Firstly, the application of the entropy weight method relies on the sufficiency and accuracy of the data, but in practice, some key data may be incomplete or biased, which could affect the accuracy of the evaluation results. Moreover, while the entropy weight method has advantages in integrating multidimensional data, it may overlook potential correlations and complex interactions between different indicators. Future research could explore more sophisticated models or incorporate other data analysis methods, such as Bayesian networks or machine learning algorithms, to further enhance the precision and comprehensiveness of the evaluation. These improvements would contribute to a deeper understanding of the distribution of child-friendliness in urban areas and provide stronger support for urban planning and policy-making.

Accuracy Evaluation and Comparison of Findings to Previous Works

In the field of urban measurement, it is challenging to provide a single, precise-accuracy figure for model performance due to the inherent subjectivity involved in such analyses and variations arising from different analytical methods. To evaluate the accuracy of our model results objectively, we invited an expert in the field to conduct an independent assessment based on the collected data and the actual conditions in Heping District, Tianjin. The expert indicated that our model results align with the actual distribution of the population and commercial areas in terms of child-friendliness, reflecting the real perception and demonstrating a high degree of reliability and applicability. Additionally, we recognize the importance of incorporating objective, quantifiable metrics to enhance the credibility of the model. Therefore, in future work, we plan to integrate more objective indicators for a more comprehensive evaluation of the model's accuracy. For example, by introducing real-world data such as traffic flow and resident feedback, we can further validate the model outputs across various dimensions, thereby improving quantifiable accuracy.

We compared our findings with previous works and observed many common points. Firstly, ref. [16] suggests that urban centers, due to their higher accessibility and convenience, are more child-friendly. This aligns with our findings, which indicate that the infrastructure and services in central areas strongly support children's activities. Our research further supplements this conclusion by showing how a diversity of social support facilities, such as dedicated children's public spaces and cultural amenities, enhances child-friendliness. Ref. [16] also emphasizes the importance of road environments on child-friendliness, especially noting that cleanliness and pedestrian safety on roads directly influence children's outdoor experiences. Our study refines this by revealing the positive impact of specific environmental elements, such as the design of walkways and the arrangement of green spaces, on children's activities. By creating more suitable outdoor environments, these design details effectively improve child-friendliness.

Moreover, ref. [2] found that resident interactions and social support within communities significantly affect children's development, particularly in areas with stronger community cohesion, where children experience a heightened sense of safety and belonging. Our research supports this perspective and further identifies the key roles of factors like the frequency of community activities and the openness of public spaces in promoting child-friendliness. This demonstrates that, beyond the physical environment, the social atmosphere of a community also profoundly influences child-friendliness. By comparing and integrating these research findings, our study not only validates the conclusions of prior research but also complements the literature by emphasizing the synergy between social and environmental factors in constructing child-friendly cities.

6. Conclusions

In conclusion, this study presents an innovative approach to quantitatively evaluate the child-friendliness of urban blocks by integrating multi-source data, including POI data, SVI data, spatiotemporal big data, and NDVI data. The study applies models such as LVLM for data processing and visual result presentation. This approach not only addresses the lack of quantitative theoretical research on child-friendliness in urban planning but also provides urban planners with a practical tool to conduct city assessments and evaluations before urban renewal projects, offering a clearer understanding of the child-friendliness of urban blocks. It enhances the efficiency of planners and decision-makers and promotes more scientific and systematic practices in building child-friendly communities. Through the application of this method in the Heping District of Tianjin, China, the study demonstrates its feasibility for identifying child-friendly urban blocks over large areas, especially in high-density central urban districts, and highlights its potential for broader child-friendliness research and assessments.

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