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Walkability Perceptions and Gender Differences in Urban Fringe New Towns: A Case Study of Shanghai

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Abstract: Urban fringe areas, characterized by relatively larger community sizes and lower population densities compared to central areas, may lead to variations in walkability as well as gender differences, such as safety perception. While objective measurements have received considerable attention, further research is needed to comprehensively assess subjective perceptions of walking in the urban periphery. As a case study, we evaluated survey responses of community perceptions of "Imageability", "Enclosure", "Human scale", "Complexity" and "Safety" of Shanghai's five new towns, comparing these with responses from the central area in terms of gender difference, and analyzed influencing factors and prediction performance of machine learning (ML) models. We developed a TrueSkill-based rating system to dynamically collect audits of street view images (SVIs) from professional students and used the result to integrate with Geographic Information Systems (GIS), Computer Vision (CV), Clustering analysis, and ML algorithm for further investigation. Results show that most of the new towns' communities are perceived as moderately walkable or higher, with the city center's community exhibiting the best walkability perceptions in general. Male and female perceptions of the "Human scale" and the factors that affect it differ little, but there are significant disparities in the other four perceptions. The best-performing ML models were effective at variable explanations and generalizations, with Random Forest Regression (RFR) performing better on more perception predictions. Responses also suggest that certain street design factors, such as street openness, can positively influence walkability perceptions of women and could be prioritized in new town development and urban renewal for more inclusive and walkable cities.

Keywords: urban fringe areas; walkability perception; gender differences; street view imagery; new town

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1. Introduction

Walking plays a vital role in the transport systems of cities. Walkable streets contribute to the creation of sustainable cities by reducing the volume of vehicles on the roads, thereby mitigating greenhouse gas emissions and enhancing air quality [1]. It has also been proven to assist residents in maintaining healthy lifestyles by encouraging physical exercise and decreasing the likelihood of obesity, heart disease, and other chronic illnesses [2]. Additionally, walking-friendly streets foster interpersonal communication and community involvement by generating more public places and inspiring people to interact with their surroundings [3,4].

Urban sprawl areas are frequently criticized for their inadequate walking infrastructure and the potential negative health outcomes associated with these developments [5].

Car-friendly surroundings are believed to discourage pedestrians from walking by producing lower residential densities, minimal variation in the types of land uses, and poorly connected streets [6]. Several academics have acknowledged the prevalence of urban fringe areas, and there has been a general exploration of the topics related to evaluating and improving walking-related physical characteristics in those areas [7,8]. Conversely, some studies found that specific attributes of the urban periphery improve walkability in several regions of the world [9,10]. Some of these perceptions shifted in the wake of the COVID-19 pandemic though both desires to avoid infection, mandates for working from home, and travel distance restrictions associated with disease control. Collectively these aspects of the pandemic increased communities' interactions with their immediate neighborhood and saw an increase in the desirability of the sprawling suburb [11]. Urban fringe areas continue to be the prevailing manifestation of urbanism in numerous regions, including China [12]. Therefore, the potential of urban fringe areas in various forms and levels of density cannot be overlooked.

Differences in perceptions of walkability between men and women may be caused by diversity between peripheral urban areas and central regions in community and street scale, residential density, and population composition. For example, central areas typically exhibit a compact road network characterized by narrow roads, whereas the new urban fringe areas tend to feature a more dispersed road network with wider roads. Some researchers have studied gender differences in active travel, and their results reveal the existence of such variations [13–15]. However, there is a dearth of research on how perceptions of walkability vary between men and women in urban fringe developments, such as Shanghai's new towns. Understanding the perceptional differences between genders is crucial for planners to promote and encourage equitable active walking in the whole city.

Given the benefits of promoting a walkable and inclusive city, in this article, we chose Shanghai's five new towns, which are developed in urban sprawl, for case studies. The relationship between urban fringe areas and new towns is demonstrated as detailed in Section 2.1. Different from some objective measurements of walkability, like the "5D" theory (Density, Diversity, Design, Destination accessibility, and Distance to transit) [16] and walkability index, we applied street view images (SVIs) auditing based on the TrueSkill rating system, Geographic Information Systems (GIS), Computer Vision (CV), and Clustering analysis to measure five walkability perceptions: "Imageability", "Enclosure", "Human scale", "Complexity" and "Safety", as well as gender differences in Shanghai's five new towns and compare them with the central area. Then, we analyzed the important factors influencing walkability perceptions of males and females in new towns and evaluated the prediction performance of several machine learning (ML) models. Within this framework, we aim to address the following research questions: (1) How do the five new towns in Shanghai compare to the central area in terms of the scores of walkability perceptions? (2) Does the peripheral location of these new towns result in gender differences in people's perceived walkability? (3) If the previous question is valid, are there any variations in the factors that influence the walking perceptions between men and women? (4) Is it appropriate to use machine learning to predict walkability perceptions based on street image features and SVIs auditing?

New towns in China are generally constructed on the urban fringe areas, representing a typical urban development pattern. China has a long history of building new towns, and over the last few decades, it has undergone the most rapid urbanization ever recorded [17]. Therefore, the research on China's new towns holds universal significance and provides valuable insights for the construction endeavors of other developing nations. By studying the walkability perceptions between men and women in various regions of development, we can gain a deeper understanding of gender differences and their implications for building more inclusive walkable cities. The remaining portions of this study are structured as follows. Section 2 provides a review of the relevant literature. Section 3 introduces the data and methods used in this study. Section 4 gives the results and discussion. Finally, conclusions are presented in Section 5.

2. Literature Review

2.1. Development of China's New Towns

The new town concept, based on the Garden City model proposed by Ebenezer Howard in 1898 [18], is a mode of suburbanization popularly applied and adapted to the scale of China's high-density urban centers [19]. The majority of urban development in China since the 1950s has been concentrated on the construction of industrial satellite cities in the suburbs of some large cities [20]. The built-up area of major cities expanded quickly after the "Reform and Opening Up", and the population scale also increased significantly. By the end of the 1990s, many megacities had already started to run out of space and witnessed a decline in operating efficiency [21]. Since then, Beijing, Shanghai, Guangzhou, and other major cities have attempted to improve the urban spatial structure by planning and creating new towns. Research on China's new towns focused on the evaluation of the effectiveness of new town planning and construction [22,23], as well as the identification of new town development patterns and spatial evolution [24,25].

In China, new town development is not pervasive and uniform throughout all cities and regions. Instead, it has been concentrated and most pronounced around the dominant megacities like Shanghai [19]. Since the 1950s, there has been a concerted effort to develop and establish Shanghai's new towns for the future [26]. After more than 20 years of continuous and rapid construction, Shanghai's five new towns, including Jiading, Qingpu, Songjiang, Fengxian, and Nanhui, which are located on the periphery of the central area, have basically realized a network of roads, metro access, and coverage of bus services [27]. Previous studies on Shanghai's new towns have concentrated on development review [21,28] and transportation [29,30]. Research also has been done on urban diversity measurement [31] and green space [32]. Moreover, it is expected that more people will move into Shanghai's five new towns, and almost all the master plans and designs of those areas stress the need to develop a livable, vibrant, and humane urban environment that prioritizes walking [33]. Although certain strategies have been proposed from the perspective of pedestrian system planning to enhance the vitality of the Jiading new town [34], there is still a need for increased attention to the walkability of urban fringe new towns.

2.2. Walkability and Gender

However, compared to the central urban area, the relatively larger community scale and lower population density of fringe areas may have caused different perceptions of the walking environment between genders. Globally, both government and non-government organizations place a high priority on investigating these differences [35]. Several studies show that women are more likely to walk than men [36,37]. Some of these variations stem from differences in walking goals. For example, females report a higher prevalence of walking purposes for fun, exercise, and leisure than males do when all ages are taken into account [38]. Females are also reported to be more sensitive to walking distance when it comes to commuting, while males appear to be more negatively impacted by travel distance when shopping [39].

Some researchers in various countries have identified objective physical environmental factors associated with gender differences in walking [40,41]. For example, in an Australian study, neighborhood walking was positively correlated with the convenience of facilities and access to services for males, while it was correlated with the former for females [41]. There are also disparities in walkability perception, particularly in safety, which extend beyond concerns solely related to darkness. Females tend to feel more vulnerable and have more concerns about their safety than males [13,42], and they feel less safe in disorderly places with rubbish and graffiti, as well as overgrown or excessive shrubbery [43–45]. Females also perceive less safety in urban center areas than males in some regions [13,46]. In addition, prior literature has shown that improving walkability based on safety and aesthetics promotes active recreational walking for older women but is not associated with men [47]. Though we have ample research evidence to prove that females' safety perceptions differ from males, we lack a clear understanding of gender inequality in other important perceptions of walkability.

2.3. Measures of Walkability in Urban Fringe Areas

The majority of current objective research related to urban fringe areas' walkability focused on assessing the attributes of accessibility and connectivity using methods such as Urban Network Analysis (UNA) [7], Space Syntax [48,49], and audit instruments [50,51]. This is mainly because these two attributes are generally considered unable to reach high levels in traditionally low-density, car-centric, street-fragmented suburbs. However, walkability, which has a more complex relationship with perceptions of people, cannot be entirely represented by physical characteristics alone. Using questionnaires is a traditional subjective approach to measuring perceptions of walking in suburban areas. For example, Leung [52] conducted interviews with pedestrians in Tung Chung, a new town in Hong Kong, to learn about the general public views of the pedestrian environment. Hooper et al. [53] evaluated urban planning for greenfield suburban developments designed to encourage walking and physical activity in Perth, Western Australia, using the "Neighbourhood Physical Activity Questionnaire" (NPAQ). However, the limitation of using traditional questionnaires is that they are expensive and labor-intensive.

More recent studies have made use of open-source big data and AI algorithms, such as SVIs data and CV, to evaluate perceptions of neighborhood street walkability [54–57] but were less focused on peripheral urban areas. These studies are limited to relying on objective indicators and cannot capture the nuanced human experiences of walking. SVIs auditing, which is cheaper and more efficient than traditional on-site auditing, has been proven a reliable method for measuring perceptions [58–60]. For example, Zhou et al. [61] distributed 186 online questionnaires based on Shenzhen's Baidu street views and analyzed them by a numeric scale to validate the visual walkability index (VWI), which was proposed in the article. "Place Pulse 2.0", a project launched by the MIT Media Lab, gathered millions of human responses for the street images, and participants were asked to select one of the two images in reaction to several perception-related questions [62]. Using the MIT Place Pulse dataset, Zhang et al. [63] predicted six human perceptual indicators in Beijing and Shanghai and concluded that the downtown areas are deemed to be more "safe" and "lively" than the surrounding suburbs. These studies present a limitation in that they were mainly concentrated on central areas, with fewer studies focusing on the urban fringe.

Currently, there is a lack of research into the perception of the street environment and walkability in China's new towns. These are locations with the greatest potential for change as they are still under development and are thus highly suitable for creating a more inclusive and walkable environment. In addition, previous studies tend to investigate gender differences in walkability from the safety perspective, while the research on the more comprehensive investigation, including multiple aspects, is less conducted. The last point is that utilizing SVIs audits and machine learning algorithms would greatly enhance the understanding of the gender differences in perceptions of walkability in urban fringe areas through quantitative methods.

3. Data and Methodology

3.1. Analytical Framework and Study Area

3.1.1. Analytical Framework

Given the increasing popularity of crowdsourcing techniques, there has been some research in recent years using subjective audits of SVIs to assess and predict human perception [63,64]. Based on previous studies, this study proposes a novel framework (Figure 1). SVIs auditing, GIS, CV, clustering analysis, and ML were combined to evaluate communities' walkability perceptions and explore the factors influencing gender differences. Additionally, the performance of ML models in predicting these perceptions was assessed. Nine communities were selected from Shanghai's five new towns and two communities from

Shanghai's central area for comparison (Figure 2a). SVIs were obtained from Baidu Maps for each community within a 15 min walking circle calculated on ArcGIS. Then, an online platform based on the Microsoft TrueSkill ranking system was developed to collect perceptions of five walkability aspects from expert students. Semantic segmentation and instance segmentation models were applied to extract the physical features in the streetscape. After that, we conducted a clustering analysis of the perceived walkability scores in 11 communities, exploring the characteristics of each cluster and the gender differences in walkability perceptions. Then we used Gini importance, which was calculated by Random Forest, to analyze the factors influencing males' and females' walkability perceptions in new towns. Finally, we compared the prediction performance of several ML models for both males' and females' perceptions of walkability.

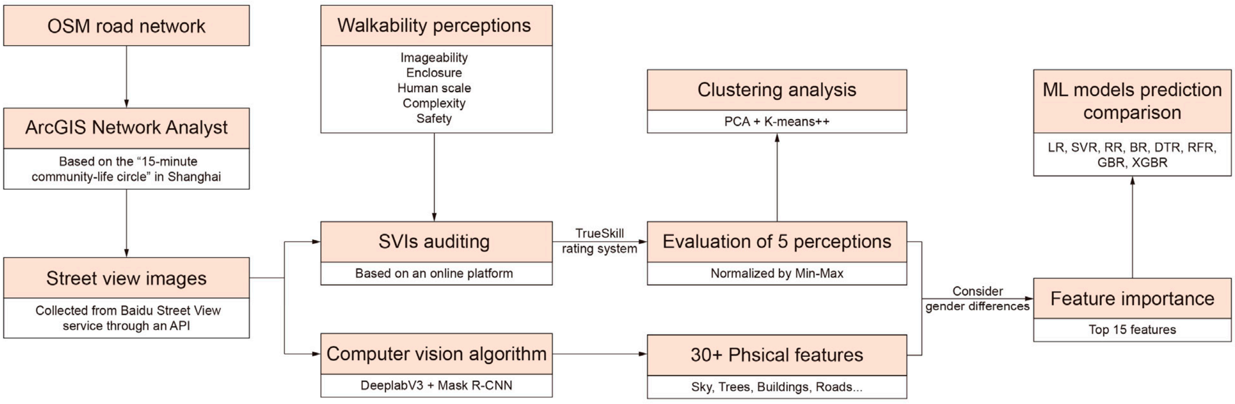

Figure 1. Analytical framework showing main methods and workflow.

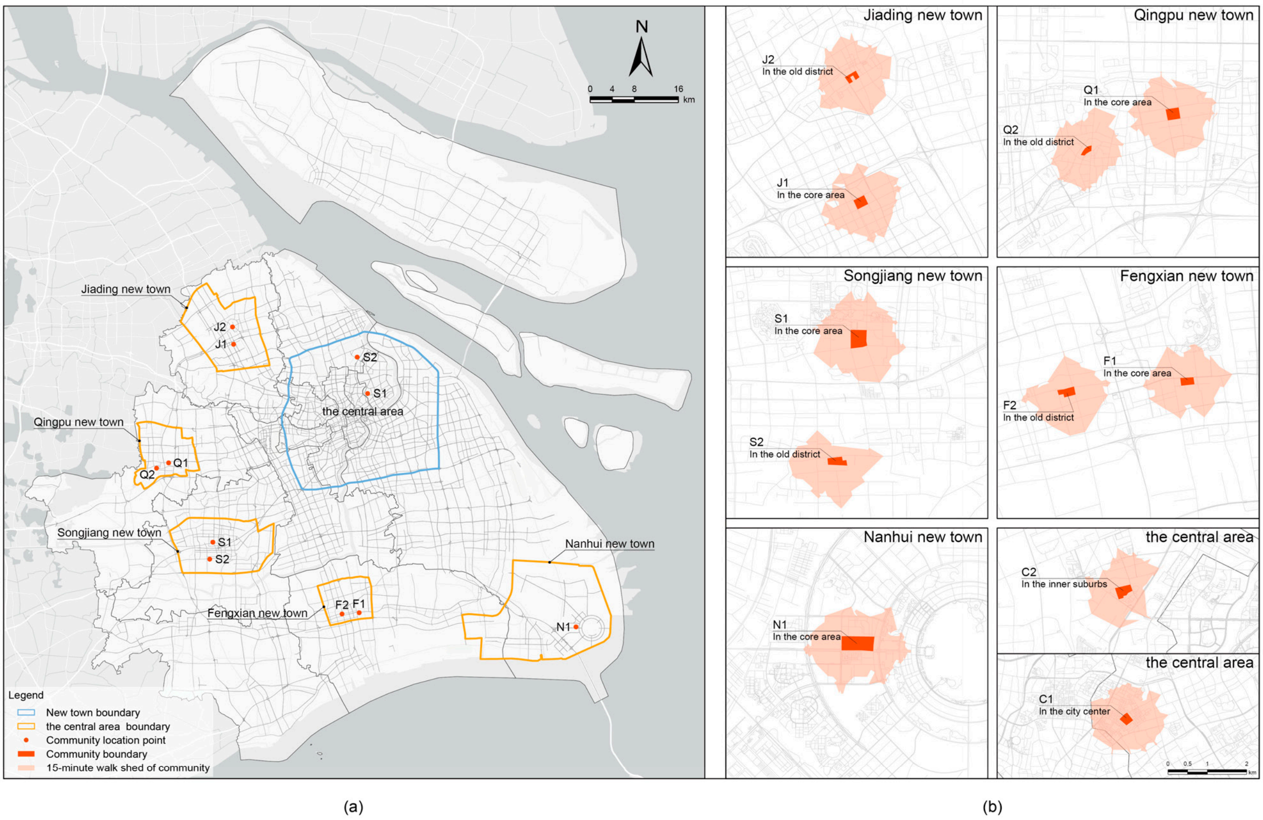

Figure 2. Study areas. (**a**) Location of Shanghai's five new towns, the central area, and 11 communities. (**b**) Range of 15 min walking circle of 11 communities.

3.1.2. Study Area

The "Shanghai 2035" [65] master planning document establishes a 4 level urban and rural system, as an important part of which Shanghai's five new towns situated on the periphery of the central area and mostly developed through new construction, are a spatial carrier reflecting the development goals of the state and local administrations. They are becoming cities with full socioeconomic functions that are spatially and functionally relatively independent of the central area. According to the master plan, all five new towns have a clear core area for new urban development, and four of the five towns have old districts, except Nanhui new town [33]. Among the central area within the Outer Ring Road, there is also a distinction between the city center and the inner suburbs. To reflect as comprehensively as possible the pedestrian environment characteristics of Shanghai's new towns compared with the central area, 11 community samples are chosen for this study, with consideration given to the variations in the geographic settings and development periods (Figure 2a). The "15-min community-life circle" promoted by the local government is a basic unit for community life in Shanghai and intends to offer basic public services to each community within 15 min walking distance. Therefore, we used the Network Analysis tool in ArcGIS to obtain the 15 min walking distance of each community based on the road network from Open Street Map (OSM) as the range of residents' daily walking activities (Figure 2b).

3.2. Data and Variables Calculation

3.2.1. Obtaining Streets Image Views

SVIs data is frequently used to measure perceptions of street walkability [66,67], and SVIs audit has been proven to be an ideal approach to assess how people feel about the micro-level street environment [61,68,69]. The SVIs of study areas were collected from the Baidu Street View service through an API. At an interval of 100 m, the sampling locations used to request SVIs were generated along the road network. For each location point, the detailed request parameters were set as follows: image size: 800 × 400, the horizontal field of view: 120 degrees, and the up or down angle of the camera: 0 degrees. Given that the majority of the study areas are in new towns with broad roads, the front view from a moving car cannot accurately depict how people perceive the sidewalk. Therefore, we adopt the right viewpoint parallel to the street section, which is more approximated to the scale of the walking environment. In total, 519 images were collected from study areas. Then, several students majoring in architecture or urban planning were invited to select the images which better fit the pedestrian perspective, and 325 images were chosen in the end.

3.2.2. Collecting Subjective Perceptions of Walkability

Beginning with urban design theory related to walkability [70], we selected four design attributes: "Imageability", "Enclosure", "Human scale", and "Complexity". In addition, many studies cited "Safety" as one of the influencing factors affecting walkability [13,71,72]. These five qualities were chosen to present subjective perceptions of walkability on street views.

We created a platform (http://120.25.231.168/web2/ (accessed on 3 April 2023)) for an online questionnaire with 62 participants, a gender ratio of approx. 1.2:1 (female = 34, male = 28). All participants are students majoring in architecture or urban planning. The survey used the format and wording of the standard Chinese Census question on gender, which is defined by the physical manifestations of the underlying biological differences. They answered questions such as "What is your gender" and "Which place makes you feel the walking environment here is more imageable" (Figure 3). They could choose their preference from two randomly presented images in five perceptions, and the sample size of 325 images is suitable for balancing survey validity, model accuracy, and raters' effort [73]. The pairwise votes were converted to ranking scores by using TrueSkill [74], a Bayesian skill rating system that is more flexible than the Elo rating system and has been applied in some urban studies [64,68]. In four days, we collected a total of 5474 pairwise scores (females' = 2985, males' = 2489) and compared each image an average of 33 times (females' = 18, males' = 15), which is sufficient to train a good TrueSkill model [75].

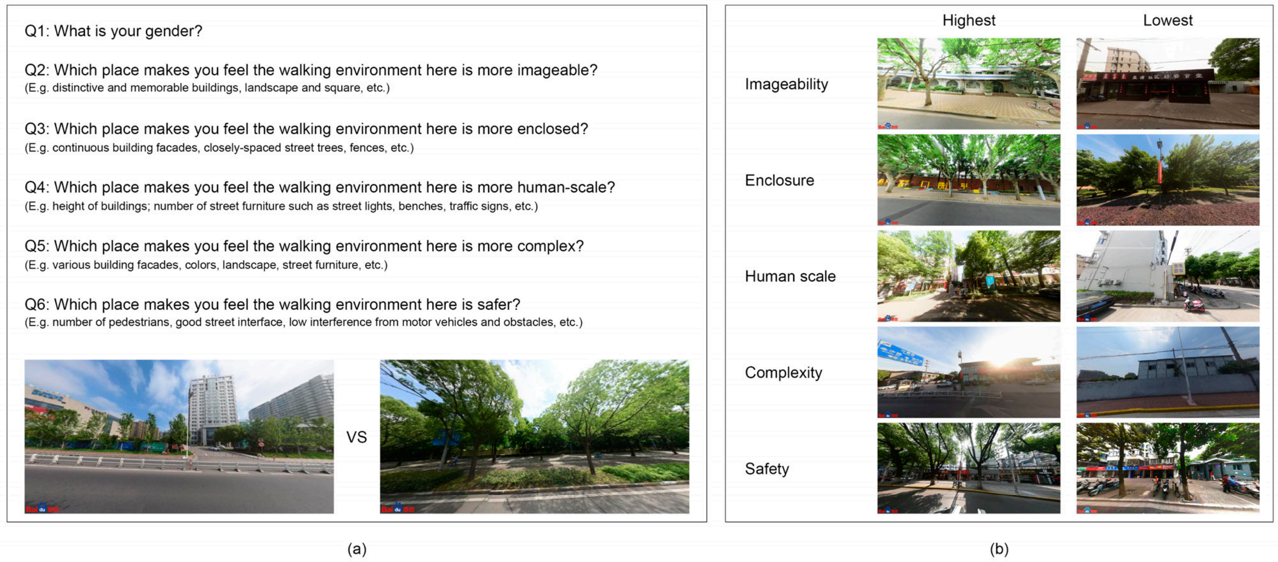

Figure 3. Collecting walkability perceptions with an online survey platform (The Chinese term "地图" means "map"). (**a**) Survey questions. (**b**) Highest-score and lowest-score example images.

3.2.3. Calculating Physical Features

The elements of street image views were extracted by DeeplabV3 [76], which is a widely used image semantic segmentation algorithm in urban research areas [77,78]. Specifically, we used the DeeplabV3 that was pre-trained on ADE20K, an image database containing more than 25,000 images and a total of 150 semantic categories. Then, we calculated the proportion of each street view element in each image (Figure 4a). In addition, Mask R-CNN [79], an advanced Convolutional Neural Network (CNN) for image and instance segmentation pre-trained on the MS COCO dataset, was applied to count the number of elements in the images (Figure 4b). Appendix A shows the descriptive statistics of the 34 physical features with the largest values.

Figure 4. Examples of CV segmentation results. (**a**) DeeplabV3 semantic segmentation. (**b**) Mask R-CNN instance segmentation.

3.3. Clustering Analysis

The K-means algorithm has been used in certain areas of the urban environment and geographic research because of its clear clustering structure and simple clustering process [53,80]. Compared with the K-Means algorithm, the K-Means++ algorithm optimizes the selection of clustering centers and reduces the impact of a poor selection of clustering centers [81]. In this paper, the K-Means++ clustering was carried out using the machine learning package Scikit-learn. The dataset was built from the 11 communities with their five walkability perceptions scores—i.e., a 5 × 11 matrix. Each variable was normalized before the clustering process using the Min-Max method. To improve the clustering results, principal component analysis (PCA) was used as a decomposition tool to reduce the number of features in the sample by projecting the data into a lower-dimensional space. Three distinctive methods determined the optimal number of "k" clusters and characterized the performance of clustering: the Inertia, the Silhouette coefficient, and the Calinski-Harabasz Index method.

3.4. Feature Importance

Visual elements with important effects on perceptions of walkability for both males and females in five new towns were identified using the GINI impurity coefficient approach of Random Forest [82]. The value of GINI can show how frequently a random instance will be misclassified as a measure of node impurity, so GINI can be used to assess each variable's significance [83]. The top 15 important factors were evaluated according to the order of all contributions.

3.5. Prediction Models Comparison

To examine the prediction performances of walkability perceptions in both males and females in five new towns, we created eight different ML models, including Linear Regression (LR), Support Vector Regression (SVR), Ridge Regression (RR), Bagging Regression (BR), Decision Tree Regression (DTR), Random Forest Regression (RFR), Gradient Boosting Regression (GBR), and eXtreme Gradient Boosting Regression (XGBR). The use of different algorithms to evaluate the prediction performance allows for better application of the dataset [68]. The models we selected are classical and well-established in supervised learning. They have been widely used as predictions based on street image feature in urban-related studies [84,85]. The dependent variables, five for males and five for females, were perceived walkability scores obtained through the online questionnaire collection platform; the independent variables were the top 15 influencing factors of each model evaluated by GINI. The Root Mean Square Error (RMSE) and coefficient of determination (R^2) were used to assess these models. The RMSE penalized big mistakes, whereas the R^2 explains model fit.

4. Results and Discussion

4.1. Clustering Results

Clustering algorithms, including K-means++ and PCA + K-means++, were implemented for clustering values from 2 to 9. The inertia, silhouette coefficient, and Calinski-Harabasz Index of clustering results were summarized in Table 1. Compared with K-means++, PCA + K-means++ significantly improved the clustering results. The mean inertia reduced from 1.152 to 0.193, the mean silhouette coefficient increased from 0.155 to 0.514, and the mean Calinski-Harabasz Index increased from 5.925 to 454.084. Therefore, we used the PCA + K-means++ algorithm to determine the final k value.

Table 1. Clustering evaluation comparison.

Clusters	K-Means++			PCA + K-Means++		
	Inertia	Silhouette Coefficient	Calinski-Harabasz Index	Inertia	Silhouette Coefficient	Calinski-Harabasz Index
2	2.886	0.264	5.959	0.869	0.569	19.504
3	2.073	0.220	5.255	0.327	0.546	29.637
4	1.501	0.137	4.928	0.132	0.551	46.170
5	1.083	0.166	5.143	0.039	0.621	104.619
6	0.732	0.122	5.553	0.167	0.558	163.410
7	0.511	0.109	5.593	0.008	0.498	237.419
8	0.289	0.128	6.681	0.001	0.452	1561.310
9	0.140	0.095	8.290	0.000	0.314	1470.603
Mean	1.152	0.155	5.925	0.193	0.514	454.084

Figure 5 shows the changes in Inertia and Silhouette coefficient when the k value is in the range of 2–9. The result of inertia shows a downward trend, and the silhouette coefficient first decreases and then increases, reaching its maximum value at k = 5, which indicates that five clusters are the ideal number. At the same time, the elbow graph reaches the inflection point, and the inertia is relatively small, so the optimal number of clusters is five. Then, we set K = 5 and performed PCA + K-means++ clustering.

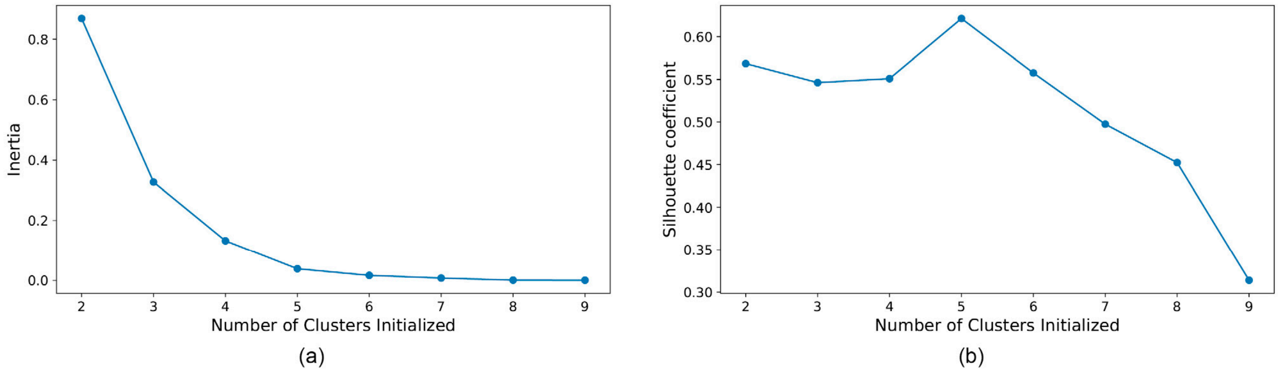

Figure 5. Changes of (**a**) inertia and (**b**) silhouette coefficient when K at 2–9, showing the optimal number of clusters is 5.

The 11 communities were well graded for their perceived walkability perception evaluation scores, and the number of communities in each cluster is relatively balanced. The results of the clusters' centroids are shown in Table 2. Cluster 0 has only one community, and the scores of the five perceptions are the highest. Each of clusters 1 and 2 has three communities, whereas clusters 3 and 4 each have two. Except for complexity, cluster 4 has the lowest score of the other four perceptions.

Table 2. Results of the clusters' centroids.

Clusters	Imageability	Enclosure	Human Scale	Complexity	Safety	Counts	Percentage
0	0.973	1.000	1.000	1.000	1.000	1	0.091
1	0.790	0.722	0.663	0.714	0.595	3	0.273
2	0.752	0.294	0.864	0.523	0.427	3	0.273
3	0.613	0.279	0.545	0.184	0.311	2	0.182
4	0.039	0.206	0.340	0.274	0.252	2	0.182

4.2. Characteristics of Communities in Each Cluster

As shown in Figure 6, the clustering algorithm was successful in identifying the communities in central areas and urban fringe areas. Moreover, the streetscape feature distribution can contribute to a deeper understanding of the built environment attributes within each cluster (Figure 7).

Cluster 0: comprises only one community—C1—which is characterized as the community in the city center with the highest walkability perception scores. Except for imageability, the other four perception scores are the highest. C1 is one of the earliest new estates for workers in Shanghai. It was built in the 1970s and is located in the densely populated area of Yangpu District. In comparison to other communities, it has a much lower average sky openness ratio with a concentrated distribution and a greater average building coverage ratio, which means the great majority of streets in the city center are less open, and that may lead to a strong sense of occlusion in visual perception. The average number of persons and motorcycles is also the highest, indicating that the population of the city center is larger than that of other urban fringe areas. The mean pavement ratio is also higher but lower than in Q2.

Cluster 1 comprises three communities—C1, F1, and F2—which are characterized as communities in new towns with high and relatively balanced walkability perception scores.

It can be found that both communities in the core and old district of Fengxian new town scored highly, suggesting that the construction and development of this new town also take into account the urban renewal of the old district. These communities have samples with a high ratio of walls in the streetscapes, and clusters 2–4 share the same condition. The reason may be that in the urban fringe areas, the communities are typically enclosed and have more walls that define distinct spatial boundaries. There are also samples with a high ratio of streetlights, indicating that some streets in the new towns have a high density of streetlights and well-planned infrastructure construction.

Cluster 2 comprises three communities—S1, J2, and Q2—which are characterized as communities in new towns with medium walkability perception scores and low scores in one perception generally. For example, the complexity score of S1 is only 0.137, and the Enclosure score of Q2 is only 0.219. Considering the communities included in cluster 1, the walkability perceptions of most communities in new towns are at a moderate or higher level. The communities in this cluster have the highest average proportion of trees, and the green environment in the new towns, especially in the old districts, is better than that in the central area when considering other communities. Meanwhile, except for F2, communities in old districts of other new towns and the city center all have a relatively large ratio of poles, which may occupy the space of pedestrian walkways and affect the overall street interface. This is likely because the poles there were put up earlier, but as the power industry develops, more and more streets were built with fewer poles to preserve the aesthetics of the community while also enhancing traffic safety and comfort. In addition, these three communities have samples with a large proportion of cars, and it was found that there are parking lots set up along the roadside upon the examination of the original streetscapes.

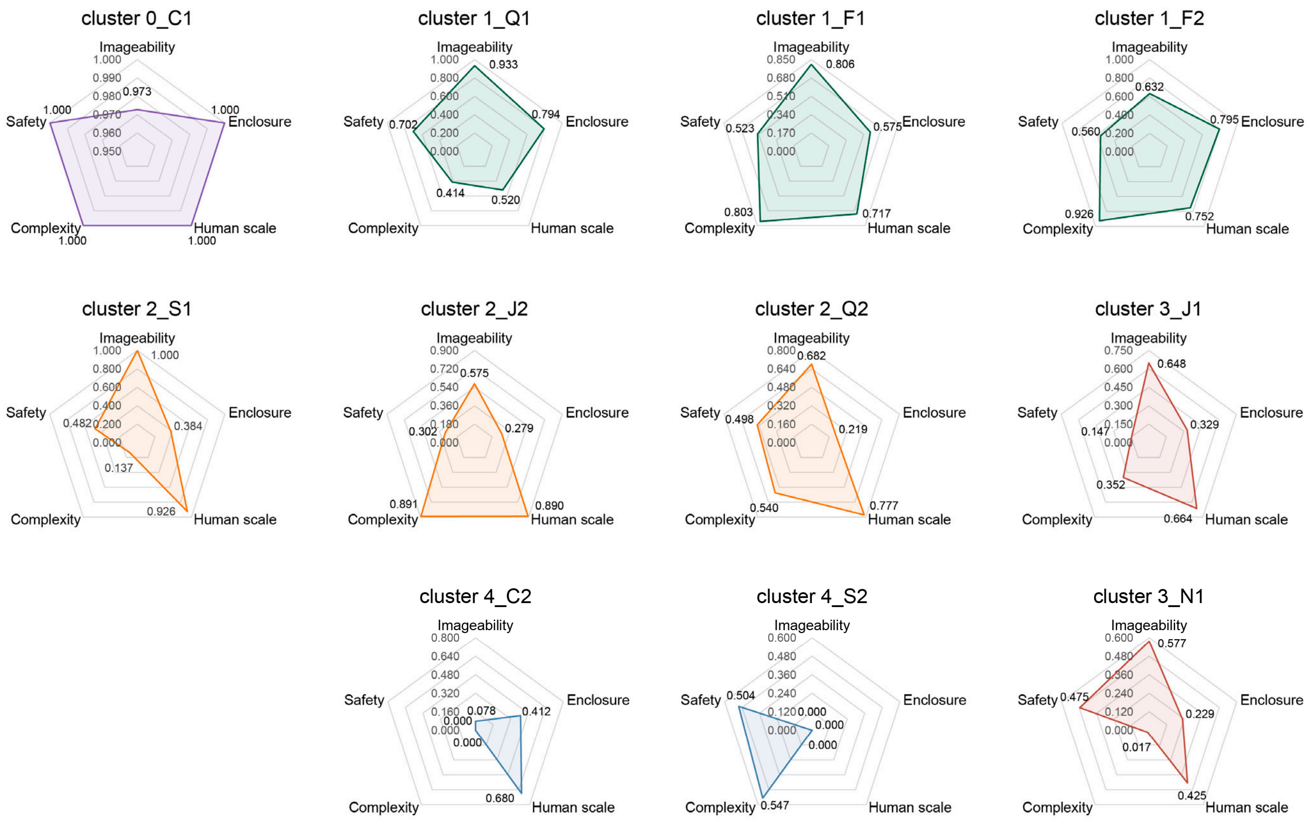

Figure 6. Clustering results of walkability perceptions for 11 communities.

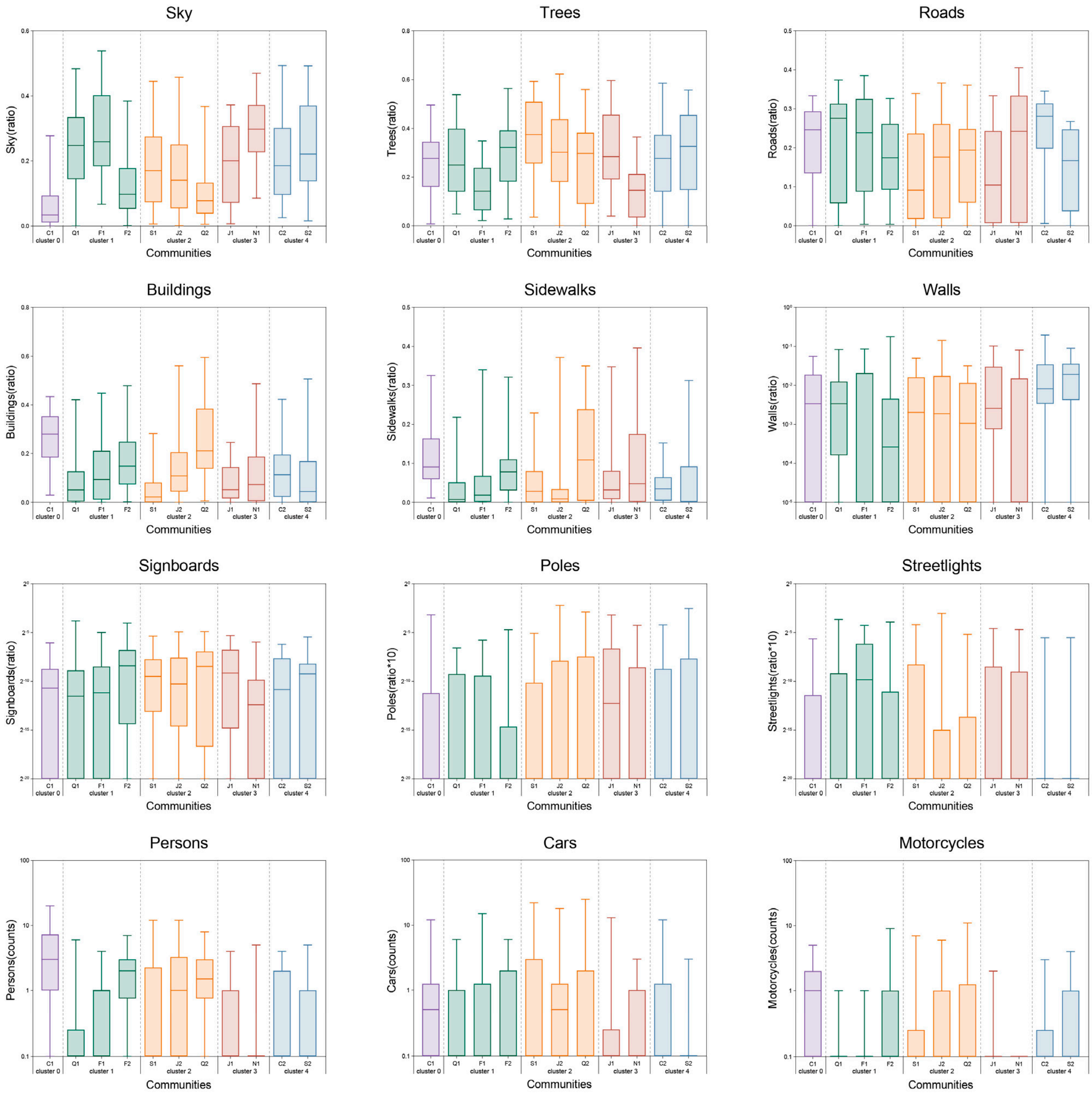

Figure 7. Descriptive analysis of typical physical features.

Cluster 3 comprises two communities—J1 and N1—which are characterized as communities in the core district of new towns with lower walkability perception scores. For instance, the complexity score of N1 is only 0.017, indicating that there is still great space for developing walkability perceptions in the core area of some new towns. When additional communities are taken into account, it is discovered that, except for the community in the city center, all other communities have a high average ratio of sky coverage, with N1 having the highest. This implies that urban peripheral areas with high street openness have a lower development density. These two communities and other communities in the core districts of new towns have a small number of persons, motorbikes, and cars on their streets, indicating that the problem of insufficient popularity persists there.

Cluster 4 comprises two communities—C2 and S2—which are characterized as communities in the edge areas with poor walkability perception scores, and the worst scores of all five perceptions are in this cluster. C2 is located in the fringe of the central area, between the city center and new towns, but its walkability perception scores are lower than most communities in new towns, with safety and complexity scores being the worst among all communities and the average ratio of roads being the highest. This suggests that the sustainable development of other peripheral areas closer to the city center is probably going to be disregarded in comparison to new towns where the government promotes progress and has relatively independent development groups. S2 is close to the Cangcheng historical and cultural district of Songjiang new town, with the lowest scores in imageability, enclosure, and human scale among all communities. The community's average ratio of walls in the streetscapes is the highest, while the average ratio of sidewalks is the lowest. Presumably, the area is quite desolate due to the numerous old, unoccupied buildings that need to be restored and rebuilt, as well as the fact that many of the original inhabitants have already moved away.

4.3. Gender Differences in Walkability Perceptions

Figure 8 shows the perceptual gender differences in five walkability aspects in various clusters. An interesting finding is that for imageability, cluster 0 has the highest score for males and the lowest score for females. Cluster 1 has the highest imageability score for females, indicating that women are more likely to be imageable about new towns with new buildings and square spaces, while men are more about the city center. Most previous literature has suggested that the fringe areas are generally less imaginable [86,87], but our finding supports this only in terms of male perception. There are also studies showing that the imageability of some newer suburbs is well-liked by people, which is consistent with the female perception in our study area [88]. For enclosures and human scales, cluster 0 has the highest scores for both males and females, which means the city center has a superior performance in these two perceptions, and these have been proved in previous studies [89,90]. Unlike males who appear to believe that the enclosure score of peripheral communities in cluster 4 is the lowest, results suggest that women think it is higher. The ranking of human scale scores for different clusters is consistent between males and females, and overall, they predominantly responded that the city center and the old districts in new towns are more humane than the core areas of the new towns.

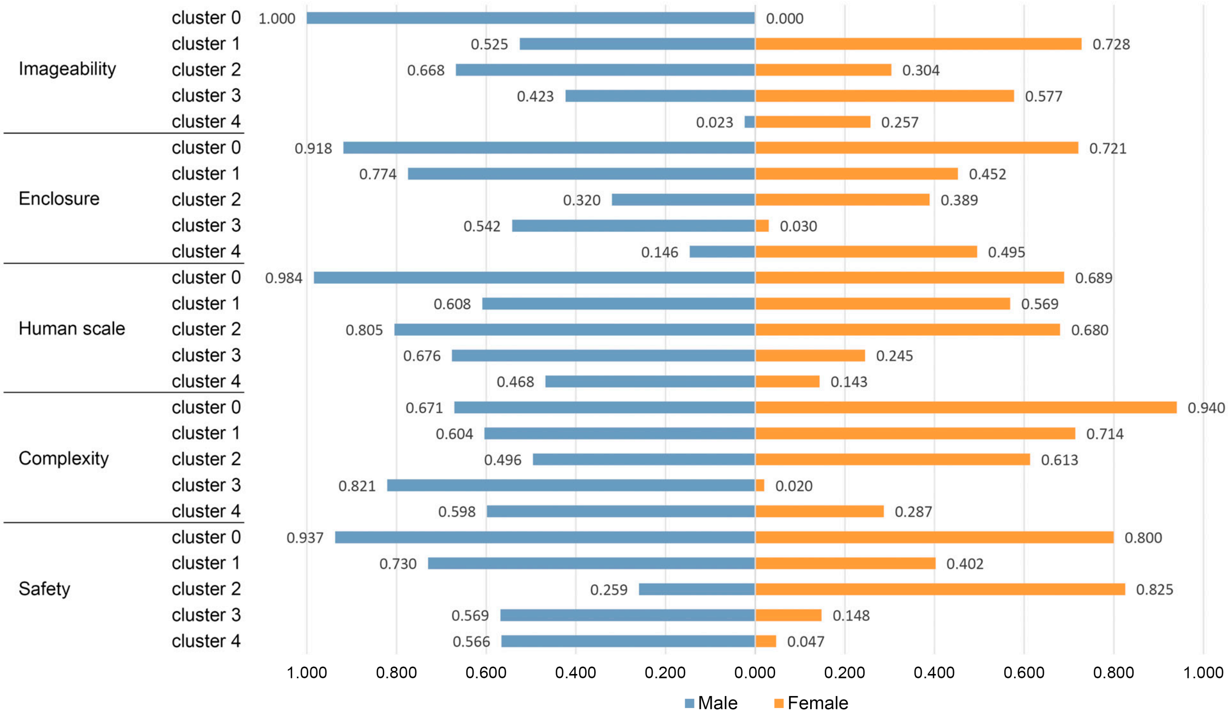

Figure 8. Walkability perception scores for five clusters of males and females.

There are significant differences in the perception of complexity between males and females. Males feel that cluster 3 has the greatest complexity score, whereas females think cluster 0 has the highest score and cluster 3 the lowest. In other words, men think some core areas in new towns are the most complex, whereas women believe the contrary. There are also gender differences in safety perception. Clusters 0 and 2 had approximately the same safety perception among females, and cluster 4 had the lowest rating. This indicates that while men think the fringe communities are relatively safe, women believe that the city center and the old districts of new towns are generally safer and peripheral communities are the worst, consistent with the results of prior literature examining some suburbs [91].

4.4. Gender Differences of Influence Factors in New Towns

The existence of gender differences can be discerned from the influencing factors that affect walkability perceptions (Figure 9). The greatest influencing factor on men's imageability is the trees, while for women is the roads. Sky has a significant impact on the imageability of both men and women. It has been proven that a higher sky ratio is associated with higher imageability in some areas [89,92]. However, combined with the results in Sections 4.2 and 4.3, the high sky ratio only has a positive impact on the imageability of women in our study, while it has a negative impact on men. In other words, women believe that new towns with high street openness are more imageable, while men believe the opposite. Lower openness of the sky generally leads to higher enclosure scores [89,93], and our findings support it more specifically. The effect of the sky on women's enclosure is significantly higher than other features, and it has a negative impact combined with the results in Sections 4.2 and 4.3. For men, features such as the sky, trees, and signboards have a similar impact on the enclosure.

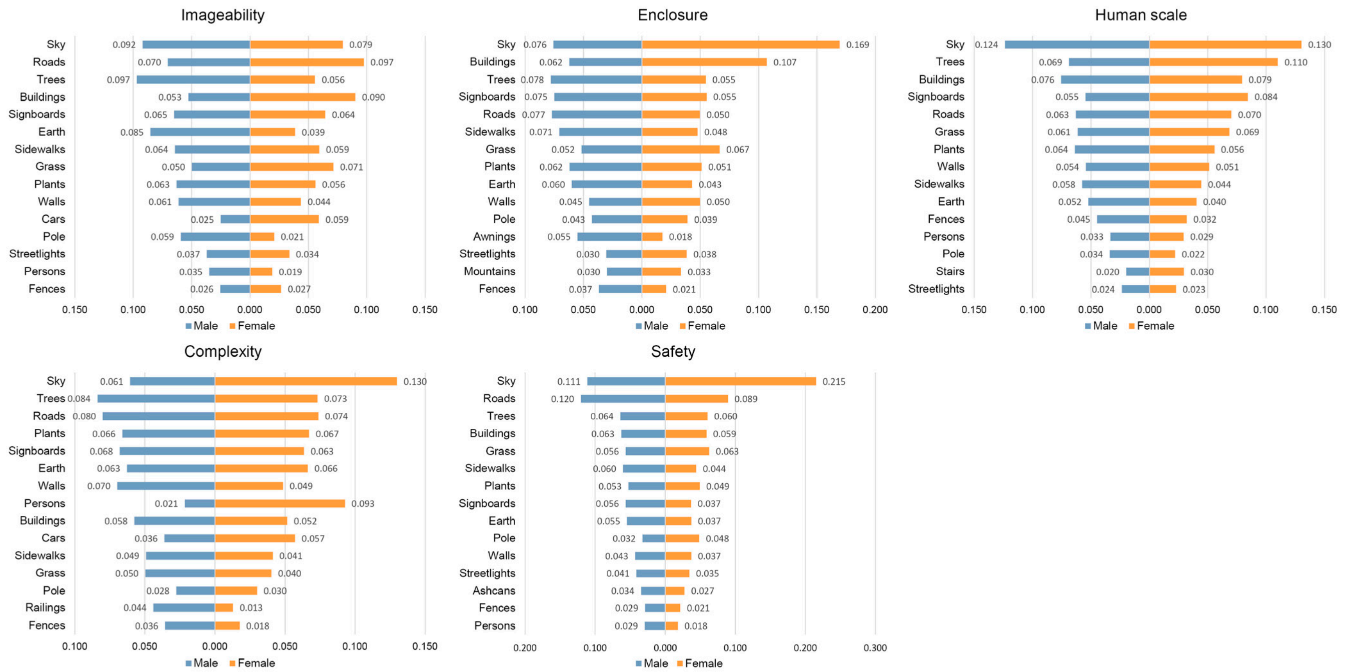

Figure 9. Scores for the top 15 important features affecting five perceptions of males and females.

The important features that affect the human scale of males and females are basically the same, with the sky, trees, and buildings having the greatest impact; similar results were also found in other studies [68,94]. Combined with the results in Sections 4.2 and 4.3, there is relatively little gender difference in the perception of human scale between males and females, and among the influencing factors, the sky has a negative impact, while trees and buildings have a positive impact. In addition, the sky and persons are the greatest factors affecting women's complexity, and the sky has a negative impact, whereas persons have a positive impact combined with the results in Sections 4.2 and 4.3. However, persons have minimal impact on men's complexity, with trees and roads having the greatest impact.

The sky has been proven by some studies to be the most influential feature of the streetscape in terms of safety [63,64,92]. Specifically, in our study, the impact of the sky on females' safety is significantly higher than other features, and males' safety is most affected by the sky and roads. Combined with the results in Sections 4.2 and 4.3, the sky has a negative impact both on females' and males' safety. Therefore, building heights and setbacks that increase sky-view could be considered to create more inclusive built environments, and urban canyons or sky view factor (SVF) measurements are suggested to be included in the planning of new towns and urban renewal of old areas. Meanwhile, ashcans only appear among the top 15 important features affecting safety perception, and the streetlights' ranking has also increased. This finding indicates that compared to other perceptions, street furniture has a greater impact on the safety perception of males and females, which is supported by previous studies [95].

4.5. Results of Models Performance

Tables 3 and 4 show the performance of different ML models, and each model performs differently in predicting walkability perceptions for males and females in new towns. Specifically, RFR outperformed other models in predicting males' enclosure, human scale, complexity, and females' imageability. RR outperformed other models in predicting females' enclosure, complexity, and safety. In terms of predicting males' safety and females' human scale, SVR performed better than other models. GBR only performed better in predicting males' imageability. The results in best models with RMSE being between 0.1400 to 0.1851 and with R^2 from 0.5947 to 0.6398. It indicates that the influencing factors in the models explain more than half of the variation in the dependent variables, which is relatively higher or close to the results of previous studies with similar sample sizes [73,90]. Therefore, the models can be applied to the large-scale measurement of the five walkability perceptions of males and females in new towns.

Table 3. Performance of different machine learning models for males' five perceptions.

Model	Imageability		Enclosure		Human Scale		Complexity		Safety	
	RMSE	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**
LR	0.1590	0.6208	0.1660	0.6138	0.2107	0.5691	0.2044	0.5754	0.1876	0.5922
SVR	0.1473	0.6325	0.1802	0.5996	0.2137	0.5661	0.1990	0.5808	* **0.1720**	* **0.6078**
RR	0.1520	0.6278	0.1701	0.6097	0.2040	0.5758	0.2043	0.5755	0.1731	0.6067
BR	0.1494	0.6304	0.1962	0.5836	0.2132	0.5666	0.2138	0.5660	0.2054	0.5744
DTR	0.2394	0.5404	0.2193	0.5605	0.2870	0.4928	0.2757	0.5041	0.2694	0.5104
RFR	0.1664	0.6134	* **0.1541**	* **0.6257**	* **0.1685**	* **0.6113**	* **0.1851**	* **0.5947**	0.2062	0.5736
GBR	* **0.1448**	* **0.6350**	0.1822	0.5976	0.2314	0.5484	0.2165	0.5633	0.1812	0.5986
XGBR	0.1554	0.6244	0.1883	0.5915	0.2442	0.5356	0.1975	0.5823	0.2024	0.5774

* Indicates the best performance model for each prediction.

Table 4. Performance of different machine learning models for females' five perceptions.

Model	Imageability		Enclosure		Human Scale		Complexity		Safety	
	RMSE	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**	**RMSE**	**R^2**
LR	0.1698	0.6100	0.1480	0.6318	0.1638	0.6160	0.1827	0.5971	0.1667	0.6131
SVR	0.1631	0.6167	0.1432	0.6366	* **0.1636**	* **0.6162**	0.1936	0.5862	0.1710	0.6088
RR	0.1605	0.6193	* **0.1400**	* **0.6398**	0.1676	0.6122	* **0.1819**	* **0.5979**	* **0.1665**	* **0.6133**
BR	0.1774	0.6024	0.1699	0.6099	0.1654	0.6144	0.1974	0.5824	0.1957	0.5841
DTR	0.2063	0.5735	0.2309	0.5489	0.2122	0.5676	0.2358	0.5440	0.2491	0.5307
RFR	* **0.1526**	* **0.6272**	0.1515	0.6283	0.1638	0.6160	0.1974	0.5824	0.1708	0.6090
GBR	0.1845	0.5953	0.1674	0.6124	0.1888	0.5910	0.1932	0.5866	0.1887	0.5911
XGBR	0.1937	0.5861	0.1811	0.5987	0.1767	0.6031	0.1954	0.5844	0.1967	0.5831

* Indicates the best performance model for each prediction.

4.6. Implications for Urban Planning and Design

The findings and framework of our study are valuable for researchers, policymakers, urban planners, and designers. They have the potential to inform practical applications in urban master planning, new town construction, and urban renewal. First, the results have indicated that many new towns have higher walkability perception scores, while the inner suburban areas have the worst perceptions of walkability. Therefore, policymakers and urban planners should not only focus on the construction and development of new towns but also prioritize other relatively peripheral areas in the city. This will allow for better formulation of urban policies and the promotion of sustainable and equitable urban development. Second, it is critical to acknowledge the differences between genders in the walkability perception. For example, sky openness has the opposite effect on the perception of imageability for men and women, so planners and designers need to deal well with it to create more inclusive and walkable cities [92]. Third, the study focuses on exploring gender differences in perceptions of walking in urban fringe new towns. The research framework can also be applied to other group segmentation studies for a comprehensive analysis. Fourth, the SVIs auditing, based on the TrueSkill rating system, is a relatively new subjective assessment method that provides new criteria for measuring the walkability of streets and neighborhoods beyond physical characteristics [89]. It can help researchers understand human perception and emotion to better model the relationship between humans and the environment.

5. Conclusions

Walking is an important component of urban transportation systems and plays a critical role in sustainable urban development. However, most previous studies have focused on the central areas, and less attention has been paid to the walkability perceptions and gender differences in the urban fringe areas. In this study, we take Shanghai's five new towns as a case study to evaluate communities' walkability perceptions and explore gender differences, influencing factors, and prediction performance of ML models. Based on the theory of urban design [70], five variables were chosen to evaluate the perception of walkability: "Imageability", "Enclosure", "Human scale", "Complexity", and "Safety". Technically, we used an online platform based on the TrueSkill rating system for SVIs auditing and combined GIS, CV, clustering analysis, and ML.

First, in terms of the evaluation of walkability perceptions and physical characteristics of the streetscape, we found that the community in the city center has the best overall walkability and the largest population. The perceived walkability of communities in most new towns is moderate or higher, but only one new town considers the urban renewal of the old district while constructing the core area. Some of the new towns still need to work on improving walkability perceptions. An intriguing finding is that the peripheral area closer to the city center is less walkable than the majority of new towns. In terms of physical features, most new towns have a greener environment, fewer buildings, and more sky openness than the city center, and some streets of new towns have a higher density of streetlights. However, there are more poles in the old districts of new towns and the city center, which may have an impact on the pedestrian path and the street interface.

Second, in terms of gender differences in the perceptions of walkability, we found that there are fewer differences in the "Human scale" between males and females, both of whom believe the new town's core areas are less humane than its old districts and the city center. Nevertheless, gender disparities in the other four perceptions were greater. For instance, women appear to think new towns are more imageable, while men are more likely to be imageable about the city center. Results suggest that men believe some core areas of new towns are more complex, while women perceive the opposite. In addition, men appear to think the periphery areas are relatively safe, whereas women hold the contrary opinion, with the old districts considered to be safer.

Third, in terms of gender differences in the influencing factors affecting the perception of walkability in new towns, we found that the sky had a large effect on all five perceptions for both males and females but had a positive impact for women and a negative impact for men on imageability. Persons have a significant positive influence on the complexity of women, whereas having minimal effect on men. Street furniture had a greater effect on the perception of safety in males and females. However, gender disparities were less noticeable in the factors affecting the "Human scale".

Fourth, in terms of the prediction of ML models in the perceived walkability of males and females in new towns, we found that each model performed differently on five perceptions. Overall, RFR performed better on more predictions. The best-performing models had RMSE between 0.1400 to 0.1851 and R^2 between 0.5947 to 0.6398. These models are effective at variable explanations as well as generalizations, and they can be used to do extensive research in new towns.

There are some limitations to this study. First, the SVIs collected from the Baidu Street View service are not time-sensitive, and future studies may involve field acquisition of real-time street view images. Second, our data volume was limited by the scarcity of volunteer raters, involving 62 students in related majors for a sample of 325 SVIs. More participants and a larger sample size may improve the accuracy and reliability of perception assessment and prediction. Incorporating volunteers with a wider range of ages and occupations may align the assessment results more closely with the perceptions of a broader population. Third, while Shanghai exemplifies the typical development pattern of Chinese metropolises in the past decades, it would be more generalizable and interesting to include additional regions in future studies, considering the international context. Fourth, the wording for the question relating to gender in this study was based on the standard Chinese Census gender question, which is based on biological sex assigned at birth. A more inclusive approach to this question may provide an important contribution to understanding different perceptions of marginalized groups.

Generally, this study evaluated the walkability perceptions of five fringe new towns in Shanghai, a metropolitan city in China, and explored gender differences, influencing factors, and prediction performance of ML models. Comparative studies focusing on different genders and areas at various stages of development can provide insightful details for comprehensive and nuanced urban research on urbanization, walkability, inclusive cities, and other related fields. In the future, the framework and conclusions of this study can be applied to the large-scale measurement of males' and females' perceptions of walkability in China's new towns. They can also serve as a guide for the design of urban fringe areas in developing countries to create more equitable and inclusive walkable cities.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and was approved by the Institutional Review Board of North China University of Technology.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Data are available on request from the authors.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Descriptive statistics of physical features.

	Physical Features	Mean	Std	Min	Max
1	Trees	0.265	0.161	0.000	0.623
2	Sky	0.201	0.132	0.000	0.538
3	Roads	0.170	0.123	0.000	0.405
4	Buildings	0.128	0.137	0.000	0.594
5	Sidewalks	0.071	0.095	0.000	0.396
6	Earth	0.035	0.072	0.000	0.398
7	Grass	0.040	0.070	0.000	0.375
8	Plants	0.035	0.057	0.000	0.312
9	Walls	0.014	0.025	0.000	0.177
10	Signboards	0.005	0.009	0.000	0.071
11	Railings	0.003	0.019	0.000	0.240
12	Fences	0.004	0.011	0.000	0.071
13	Mountains	0.003	0.012	0.000	0.103
14	Floors	0.003	0.019	0.000	0.179
15	Paths	0.002	0.014	0.000	0.140
16	Pole	0.001	0.002	0.000	0.022
17	Sand	0.001	0.005	0.000	0.052
18	Streetlights	0.000	0.001	0.000	0.012
19	Stairs	0.000	0.001	0.000	0.019
20	Ashcans	0.000	0.000	0.000	0.005
21	Posters	0.000	0.001	0.000	0.011
22	Rocks	0.000	0.001	0.000	0.009
23	Booths	0.000	0.001	0.000	0.020
24	Bases	0.000	0.000	0.000	0.002
25	Bridges	0.000	0.000	0.000	0.006
26	Windowpanes	0.000	0.001	0.000	0.012
27	Columns	0.000	0.000	0.000	0.005
28	Runways	0.000	0.001	0.000	0.015
29	Awnings	0.000	0.000	0.000	0.004
30	Persons	1.174	1.873	0.000	12.000
31	Cars	1.377	3.318	0.000	25.000
32	Motorcycles	0.475	1.371	0.000	11.000
33	Bicycles	0.234	0.753	0.000	8.000
34	Benches	0.083	0.315	0.000	2.000

The data of the first 29 features is the proportion of each feature in the SVIs calculated by DeeplabV3, and the data of the last 5 features is the count of each feature in the SVIs calculated by Mask R-CNN.

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