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Construction of Tianjin Fashion Industry Data Analysis System under the Framework of International Consumption Center City

Bing Liu[1], Xiaohu Li[2,] ✉

[1] *Department of Fashion Art, College Of Fine Arts&Design, Tianjin Normal University, Tianjin, 300387, China*

[2] *Department of Art Painting, College Of Fine Arts&Design, Tianjin Normal University, Tianjin, 300387, China*

ABSTRACT
In the context of building an international consumption center city, it is of great significance to further study the competitiveness of the fashion industry and effectively grasp the direction and focus of the development of the fashion industry in order to promote the construction of an international consumption center city. The study adopts the entropy weight-TOPSIS method to measure the competitiveness of Tianjin's fashion industry from 2020 to 2023, and compares it with typical provinces in order to have a comprehensive understanding of its fashion industry competitiveness level. Then, the spatial structure characteristics of the distribution of fashion industry facilities in Tianjin were further explored through the kernel density analysis method and the radius of gyration analysis method. Finally, Ripley's K function is used to calculate the level of agglomeration and the range of the most significant agglomeration scale of each type of fashion industry, which summarizes the distribution characteristics of strategic fashion industries at the overall level. Horizontally, the competitiveness level of Tianjin's fashion industry shows an upward trend from 2020 to 2023, and vertically, the competitiveness level of Tianjin's fashion industry is ranked in the middle range of the country, with a certain gap between it and the strong provinces such as Jiangsu, Shandong and Guangdong. The most significant agglomeration scale of the new generation electronic information technology industry is 22,000 meters at maximum, and its DiffK value also reaches 13,317.938.

Keywords: Entropy weight-TOPSIS method, kernel density analysis, Ripley's K function, fashion industry, international consumption center city

1. Introduction

Currently, digital technology has brought systematic changes to the development of the fashion industry. Accelerating the digital transformation of fashion industry clusters is crucial for the high-quality development of the fashion industry [1-3]. The integrated development of digital technology

✉ Corresponding author.
E-mail address: meishe003540@163.com (X. Li).
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and fashion industry in China has good basic conditions and development environment. At present, it is necessary to fully utilize digital technology to promote the high-quality development of the fashion industry, cultivate the fashion industry as a new engine of consumption growth, and play a role in urban renewal and functional remodeling [4-7].

In recent years, emerging digital technologies such as 5G, big data, cloud computing, artificial intelligence, Internet of Things, and blockchain have accelerated innovation and are becoming a key force in reorganizing industrial factor resources, reshaping the structure of industrial systems, and changing the pattern of industrial competition [8-10]. Digital economy has become an important engine for promoting Chinese-style modernization and a key hand in constructing new national competitive advantages [11]. In this context, promoting the digital economy to empower the development of fashion industry is conducive to comprehensively enhancing the digital intelligence and customization capabilities of fashion manufacturing, bringing consumers a new fashion experience, further improving the management level and efficiency of the fashion industry, and promoting the integration of the fashion industry with science and technology, culture, creativity and other development [12-14].

The rise of Internet technology and mobile technology has promoted the rapid development of e-commerce and social networks, making the amount of data related to the fashion industry reach unprecedented heights, and the decision-making of the apparel industry has begun to move towards a data-driven model [15-17]. The use of big data technology to analyze the massive amount of apparel fashion data is of great value to both scientific research and the development of the apparel industry. It is not accidental that big data analytics can be applied to the field of fashion industry, because the two have strong compatibility, which is mainly rooted in three elements, data massiveness, diversity and rapidity. In addition, fashion data is also time-dependent and subjective [18-20]. Fashion itself is a part of human society and culture, so fashion data, in addition to covering physical attributes such as clothing silhouette, texture, color, etc., also has a certain subjective nature, which is affected by a combination of factors such as time and geography. The correlation of multiple factors should be taken into account in the process of fashion analysis to reduce the bias of estimation or prediction results [21-23].

Firstly, the practice of data analysis technology in the fashion industry was analyzed and examined, Song, E. Y systematically reviewed the research literature related to fashion platform big data analysis, smart fashion factory perception as well as the trend theme, the research of fashion platform and smart fashion factory is more enthusiastic, while the research focusing on the fashion consumer is less, in which the sharing of fashion platform, the creation of the research direction is very novel and popular, and pointed out that fashion intelligent factories and innovative fashion platforms are the future trend of the future of the fashion industry in the future [24]. One of the applications of data analytics in the supply chain of the fashion industry aims at, quality management and planning of fashion products. Fani, V et al. conceptualized a model to improve data analysis and visualization for quality management and applied it to the fashion industry in order to strategically modify the sample quantities of fashion product categories and materials supplied by the suppliers, and at the same time, it can provide effective suggestions for the defects existing in the fashion products, effectively improving the quality control of fashion products [25]. However, the focus of data analytics in the fashion industry is on consumers, through social media data mining and consumer behavioral perception in fashion retail stores to obtain consumer information about fashion products, in order to develop effective marketing strategies for fashion products and optimize the design of fashion products. Acharya, A et al. based on the practice of big data analytics in four fashion retail organizations have confirmed that Big data technology effectively promotes knowledge-based interactions between customers and salespeople, which facilitates the formation of a core of knowledge co-creation, supports efficient decision-making, and creates positive conditions for fashion retail organizations to achieve better performance [26]. Al-Obeidat, F et al. analyzed the practical cases of data mining techniques and sentiment analysis strategies applied in the fashion industry, and pointed out that these techniques effectively help fashion organizations to quickly identify and obtain information data such as fashion social media customer feedback, and then optimize the design of fashion products in order to satisfy the consumers and obtain more market returns [27]. Chan, C. O et al. used multimodal sensing devices to capture customer behavior in a fashion retail store and applied a fuzzy logic-based data analysis model to generate data on customers' willingness to purchase fashion products, which assisted store staff to promote fashion products to customers scientifically and rationally, and also guided and planned the generation of a fashion supply chain [28]. Singhal, V et al. conceived the FC-CBR model of consumer brand relationship and FC-CBP model of consumer brand perception to explore the factors affecting consumer brand relationship and brand perception, and subsequently the information data generated by the two models were subjected to cluster analysis in order to categorize the consumers, which in turn led to the implementation of personalized marketing to promote the purchase of consumer fashion products [29].

Based on the background of the construction of international consumption center city, the article firstly constructs the evaluation system of Tianjin fashion industry competitiveness, which contains 21 specific indicators including resources, demand, related industries, government and enterprises. Then, it combines entropy weight method and TOPSIS method to construct Tianjin fashion industry competitiveness evaluation model, and then researches the spatial evolution analysis method and spatio-temporal point pattern analysis theory, mainly combing the theoretical methods of spatial K function and spatio-temporal K function, and introduces the basic concepts and core process of K function. Finally, based on the evaluation and analysis of the competitiveness of Tianjin's fashion industry, the spatial evolution characteristics of Tianjin are studied by comprehensively applying the methods of average city center distance and spatial dispersion index, radius of gyration and spatial distribution curves, and kernel density analysis, to summarize the general law of the spatial evolution of Tianjin's fashion industry. Finally, through the kernel density analysis and Ripley's K function, the distribution characteristics, agglomeration degree and most significant agglomeration scale of strategic fashion industries in Tianjin at the overall level are analyzed.

2. Method

2.1. Construction of Tianjin fashion industry competitiveness evaluation index system

2.1.1. Tianjin fashion industry competitiveness evaluation index system. Based on reading a large number of domestic and foreign related research literature and reports and analyzing the factors affecting the competitiveness of the fashion industry, 24 indicators are selected. On one hand, the screening of the indicators should consider whether the indicators are relevant or not, and on the other hand, it should also consider whether the data of the indicators are available or not, and whether they can be quantified or not. After that, 15 experts in the industry were invited to score each of the selected indicators, with a range of 0 to 5. The scoring principle: if an indicator is considered extremely important, it is given a score of 5; if an indicator is considered very important, it is given a score of 4; if an indicator is considered very important, it is given a score of 4. If an indicator is considered to be very important, 4 points will be given. If an indicator is considered to be important, it is given a score of 3. If you consider an indicator to be less important, give it 2 points. If an indicator is considered unimportant, 1 point is given, and if an indicator is considered completely unimportant, 0 points are given. Finally, according to the weighted average score of each indicator, screen out the indicators with a weighted average score of more than 3 points, and establish the evaluation index system of fashion industry competitiveness of this paper by taking into account the research content of this paper. The evaluation index system of fashion industry competitiveness is shown in Table 1.

Table 1. Index system of competitive evaluation of fashion industry

Primary indicator	Numbering	Secondary indicator	Numbering
Resource elements	X1	The number of fashion industries (10,000)	X11
		The number of students in the average university is (10,000).	X12
		Postal industry revenue (100 million yuan)	X13
		More than 30,000 meters of shopping center number (1)	X14
		Whether the national Internet backbone is straight.	X15
		R&d intensity (%)	X16
Requirement element	X2	Per capita GDP (10,000)	X21
		Per capita disposable income (yuan)	X22
		Per capita consumer expenditure (yuan)	X23
		Clothing per capita consumer spending is more than (%)	X24
		Other supplies and services spend more than (%)	X25
Relevant industry and government elements	X3	The number of people's art galleries and the winnating pavilion	X31
		Museum number (1)	X32
		Number 5a scenic spots	X33
		Number of national intangible cultural heritage projects (1)	X34
		Visa exemption	X35
		Inbound travel foreign exchange income ($100 million)	X36
Corporate strategy and competitive elements	X4	The business income of the above fashion enterprises (100 million yuan)	X41
		Fashion enterprise number	X42
		The number of international luxury stores	X43
		The number of first stores in the country.	X44

2.1.2. Research Sample and Data Sources. Indicator data for Tianjin was filtered out by checking the official government website, and these indicator data are cross-section data for 2023. the number of shopping malls with more than 30,000 square meters is from the official website of Winning Business, whether the sample city is a national Internet backbone direct connection point is from the public list of the Ministry of Industry and Information Technology of the People's Republic of China, the number of 5A scenic spots is from the Ministry of Culture and Tourism of the People's Republic of China, the number of national intangible cultural heritage items is from the National Intangible Cultural Heritage Net, and the number of related fashion enterprises is calculated and organized according to the Eye of Heaven app. “The number of international brands, i.e. the number of international luxury brands, is obtained by comparing 17 brands in four product categories, namely apparel, watches, jewelry and cosmetics, with the number of stores opened in 19 sample cities by searching the brands' official websites, based on the list of Top 500 World Brands in 2023 compiled by the World Brand Lab and the Global Luxury Power Ranking in 2023 published by Deloitte. Based on the list of Top 500 World Brands 2023 compiled by the World Brand Lab and the Global Luxury Power Ranking 2023 published by Deloitte, the author selected 17 brands in the four product categories of apparel, watches, jewelry and cosmetics, and searched for the opening of stores in 19 sample cities through the official websites of the brands. The rest of the data was obtained from the 2023 Statistical Yearbook of each city.

2.2. Tianjin Fashion Industry Competitiveness Evaluation Method

2.2.1. Entropy weight TOPSIS method. With the deepening of academic research on industrial competitiveness, certain results have been achieved on the quantitative measurement methods of industrial competitiveness indicators, and in general, there are two forms of competitiveness evaluation methods, namely, single-item evaluation and comprehensive evaluation. Individual evaluation is to use economic or technical standards to evaluate a certain aspect of industrial competitiveness, which is simple and intuitive and targeted, but cannot reflect the comprehensive competitiveness of the evaluation object. Comprehensive evaluation is to combine multiple factors to quantitatively measure many aspects of industrial competitiveness, also known as multi-indicator evaluation method [30]. Since the evaluation of fashion industry competitiveness requires a comprehensive test of multiple dimensions, it is suitable to use the multi-indicator evaluation method.

TOPSIS method is a comprehensive evaluation method of multiple indicators and multiple programs, which evaluates the strengths and weaknesses of each indicator by converging and normalizing the raw data, and calculating the degree of proximity between each indicator and its respective positive ideal value (the best value) and negative ideal value (the worst value).The TOPSIS method has no requirements for sample data, and it can fully reflect the actual situation of each indicator in a system, which is It is a commonly used mathematical model in system engineering to solve the multi-objective decision analysis problem of limited program by using the distance principle.

Entropy value method is an objective assignment method, in the specific use of the process according to the degree of dispersion of the data of each indicator, using information entropy to calculate the entropy weight of each indicator, and then according to the indicators of the entropy weight to make certain corrections, so as to obtain a more objective weight of the indicators. This method can avoid the error brought by subjective assignment, so the quoted entropy value method is used to determine the weights.

2.2.2. Entropy weight TOPSIS method modeling:

1) Determination of the comprehensive score value of industrial competitiveness:

(1) Construct the original evaluation matrix. Assuming that there is n sample city for the study and m evaluation indicators, the raw data obtained from each indicator will form the following matrix A:

$$A=\begin{bmatrix} a_{11} & \cdots & a_{1m} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{mn} \end{bmatrix}_{m\times n} \tag{1}$$

(2) Data standardization. Through the polar deviation standardization will be the original data standardization processing, if the indicator is a positive indicator, through the formula for calculation: if the indicator is a reverse indicator, through the formula to speak line calculation. In order to avoid the assignment of the number of meaningless, all the results of the treatment will be shifted by 0.0001.

$$a_{ij}^{+} = \frac{a_{ij} - \min(a_{ij},...,a_{nj})}{\max(a_{ij},...,a_{nj}) - \min(a_{ij},...,a_{nj})} + 0.0001 \tag{2}$$

$$a_{ij}^{-} = \frac{\max(a_{ij},...,a_{nj}) - a_{ij}}{\max(a_{ij},...,a_{nj}) - \min(a_{ij},...,a_{nj})} + 0.0001 \tag{3}$$

(3) Calculate the weight P_{ij} of the value of the indicator for program i.

$$P_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{4}$$

(4) Calculate the information entropy of the jst indicator e_j.

$$e_j = -\frac{1}{lnm} * \sum_{i=1}^{n} P_{ij} \log(P_{ij}) \tag{5}$$

(5) Calculate the entropy redundancy g_j of the jnd indicator according to e_j. The larger the g_j, the smaller the entropy value, indicating that the indicator is more important.

$$g_j = 1 - e_j \tag{6}$$

(6) Calculate weight w_j for indicator j.

$$w_j = \frac{g_j}{\sum_{j=1}^{m} g_j} \tag{7}$$

2) Comprehensive ranking of fashion industry competitiveness:

(1) According to the weight w_j determined by the entropy value method, form a weighted normalized matrix:

$$\mathrm{Z} = \begin{bmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \cdots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{bmatrix} \begin{bmatrix} w_1 & 0 & 0 \\ \vdots & \ddots & \vdots \\ 0 & 0 & w_n \end{bmatrix} = \begin{bmatrix} f_{11} & \cdots & f_{1n} \\ \vdots & \cdots & \vdots \\ f_{m1} & \cdots & f_{mn} \end{bmatrix} \tag{8}$$

(2) Determine the positive and negative ideal solutions of the assessment objectives. The optimal value of each assessment objective is the positive ideal solution f_j^{+}, and the worst value is the negative ideal solution f_j^{-}:

$$f_j^{+} = \begin{cases} \max(f_{ij}), j \in J^{+} \\ \min(f_{ij}), j \in J^{-} \end{cases} \tag{9}$$

$$f_j^{-} = \begin{cases} \min(f_{ij}), j \in J^{+} \\ \max(f_{ij}), j \in J^{-} \end{cases} \tag{10}$$

Where J^{+} is a benefit indicator, the larger the value of the indicator the better, and J^{-} is a cost indicator, the larger the value of the indicator the more unfavorable it is to the assessment results.

(3) Calculate the distance scale. Use the n-dimensional Euclidean formula to calculate the distance

of each target value to the positive ideal solution $S+$, and the distance of each indicator to the negative ideal solution S^-. The closer the target value is to the positive ideal solution, and the further it is from the negative ideal solution, the better the evaluation target is. The closer the target value is to the positive ideal solution and the closer it is to the negative ideal solution, the worse the target is.

$$S^+ = \sqrt{\sum_{j=1}^{m} (f_{ij} - f_j^+)^2} \tag{11}$$

$$S^- = \sqrt{\sum_{j=1}^{m} (f_{ij} - f_j^-)^2} \tag{12}$$

(4) Calculate the relative closeness and rankin. Calculate the relative closeness of each evaluation objective to the ideal solution $C(0 \le C \le 1)$, the higher the closeness, the better the objective is, and rank the advantages and disadvantages accordingly [31].

$$C_i = \frac{S_i^-}{(S_i^+ + S_i^-)} \tag{13}$$

2.3. Spatial evolution analysis methods

2.3.1. Average urban center distance and spatial dispersion indices. The average city center distance is the average value of the distance from the tourist place to the city center, based on the measurement of the spatial distance of the recreational nodes from the city center point, and the number of nodes of this type, the ratio is the average city center distance of this type of nodes, and this paper calculates the value centered on Tianjin City $(X,Y) = (118.778, 32.045)$. The spatial dispersion index can reflect the strength of different types of recreational nodes constrained by distance in space, which can be expressed as the ratio of the standard deviation of the urban center distance of recreational nodes and the average urban center distance, in order to measure the fluctuation status or the degree of spatial dispersion presented by various types of recreational nodes with the change of distance.

2.3.2. Slewing radii and spatial distribution curves. The radius of gyration and the spatial distribution curve can reflect the spatial distribution differences of different types of recreational nodes. The radius of gyration is to take the center as the center and draw a circle with different spatial scales as the radius, and by changing the radius of the circle, we can get the distribution status of different types of recreational nodes in different spatial scales. The spatial distribution curve is a curve with distance (radius) as the horizontal coordinate and the number of certain types of recreational nodes at the distance as the vertical coordinate, which can be made by using Excel, and this correspondence between the number of recreational nodes and the distance can reflect the spatial distribution of different types of nodes.

2.3.3. Kernel density estimation. Kernel density estimation has the obvious advantage of analyzing point data, the method can get the density change map of recreational nodes, spatial change with continuity “peaks” and “valleys” can strengthen the display of spatial distribution patterns [32]. Its geometric significance is: density distribution in the center of each x_i point is the highest, decreasing outward, when the distance from the center to reach a certain threshold range (the edge of the window) at the density of 0. In the two-dimensional case, the core density at the center of the grid x for the density of the window range of the density and:

$$\hat{f}(x) = \frac{1}{nh^2\pi} \sum_{i=1}^{n} \left[1 - \frac{(x-x_i)^2 + (y-y_i)^2}{h} \right]^2 \tag{14}$$

where h is the threshold, n is the number of points within the threshold, and $(x-x_i)^2+(y-y_i)^2$ is the distance from point (x_i, y_i) to point (x, y). The key to kernel density estimation lies in the determination of the threshold range (the edge of the window), i.e., the bandwidth, which is usually adopted in practice by using Silverman's rule of thumb to reasonably determine the bandwidth based on the number of nodes of the recreational node and the area of the study area.

2.4. Theory of Spatio-Temporal Point Pattern Analysis

2.4.1. Estimation and simulation of the spatial Ripley's K-function. The spatial K-function is a statistical method designed around the second-order effects of spatial points. It takes into account both the number of points as well as the distance of point pairs, and is capable of quantitatively evaluating the difference between a will-observed point pattern and a random pattern at different spatial scales. The theoretical formulation of the spatial K function is shown in Eq. The K value describing the point pattern is obtained by dividing the expected total number $E(s)$ of points within a spatial distance of s by the point density λ_s (which also describes the first-order effect of spatial points):

$$K(s)=\frac{E(s)}{\lambda_s} \tag{15}$$

If the point pattern is generated by a process that conforms to a Poisson distribution (which is equivalent to a point pattern that conforms to a completely spatially random CSR), then the corresponding K value $K(s)=\pi s^2$. Thus, if the K value of the observation point is calculated as $K(s)>\pi s^2$, it means that the observation point has a higher expected number of points at spatial distances s than a point pattern that conforms to the CSR, and so it is considered to exhibit an aggregated pattern. If the K value of the observation point is calculated as $K(s)<\pi s^2$, it is considered to exhibit a discrete pattern. In practice, the K value of the point pattern can be calculated by Eq:

$$\hat{K}(s)=\frac{A}{n^2}\sum_{i=1}^{n}\sum_{j\neq 0}\frac{I_s(d_{ij})}{\omega_{ij}} \tag{16}$$

Where, A represents the area of the study area, n denotes the total number of points, d_{ij} refers to the spatial distance between point p_i and point p_j, $I_s(d_{ij})$ describes the point-to-filtering rule, and s denotes the spatial distance threshold, which can be described by Eq:

$$I_s(d_{ij})=\begin{cases}1, & (d_{ij}\le s)\\ 0, & otherwise\end{cases} \tag{17}$$

In addition, ω_{ij} in Eq. denotes the boundary effect correction weight. Border effect means that since the points outside the boundary are not included in the calculation, the total number of neighboring points may be underestimated for the points at the edge of the study area, which will lead to a bias in the calculation of the K function. Therefore, the process of calculating the K function will include the step of boundary correction weights, the specific correction methods include Border Correction, Isotropic Correction and Translation Correction. The weight of the point to (p_i, p_i) is defined as the ratio of the length of the arc of the circle centered at the point and the radius of the spatial distance to the circumference of the circle in the study area.

As shown in Eq. The K function is usually converted to a L function to more clearly determine the K value of the observed point pattern and the corresponding theoretical K value of the CSR point pattern, so as to quickly determine the characteristics of the distribution of the observed points. When the L value is 0, it indicates that the generation process of the observed points is completely random. When the L value is greater than 0, it indicates that the observed points exhibit an aggregated pattern. And when the L value is less than 0, it indicates that the observed points show a discrete pattern.

$$\hat{L}(s) = \sqrt{R(s) / \pi} - s \tag{18}$$

However, in the real world, point objects that exactly match the CSR hardly exist, so directly comparing the K values of the observed points with the theoretical K values does not provide a reliable support for analytical studies. In order to obtain statistically significant computational results, the K function will be applied not only to the computation of observed points, but also to the computation of dry simulated points. After several simulations and comparisons, the distribution pattern of observation points can be evaluated at a certain significance level. For example, if the K value/ L value of an observation point pattern is greater than the upper bound of a few values of 100 simulated point K values in the $[s_l, s_r]$ range, then there is 99% certainty that the observation point pattern exhibits a clustered pattern in the $[s_l, s_r]$ range. The main methods for generating simulated points are Monte Carlo and Bootstrapping: the former generates simulated points in a completely random manner, in other words, the simulation assumes that the point objects will appear anywhere in the study area; the latter generates simulated points from observations by back sampling, in other words, the simulation assumes that the point objects will only appear at the locations of the observations. In other words, the simulation method assumes that the point objects will only appear at the observation points. How to choose the point simulation method needs to be considered in specific application scenarios, for example, in the study of the aggregation effect of different industries, the simulation of the point pattern of one type of industry can be accomplished from the point data of the other types of industries in the form of Bootstrapping, which is able to exclude the location where the industry is completely impossible (such as the middle of the river), and get the simulation results that are more closely related to the actual situation.

In this paper, the calculation of the K function around the observation point will be referred to as "K function estimation", and the calculation of the K function around the simulation point will be referred to as "K function simulation". Both "K function estimation" and "K function simulation" need to be calculated according to Eq. As can be seen from Eq. the total number of neighboring points whose spatial distance from them is less than or equal to s needs to be calculated centering on each point of the point pattern in order to complete it. In other words, the core process of the spatial K function is a two-layer traversal, in this paper, the traversal around the center point is called "outer traversal", while the traversal around the neighboring points as "inner traversal".

On the basis of the spatial K function, many scholars have extended variants of the K function for different application scenarios, such as the spatio-temporal K function for spatio-temporal point process analysis, the network K function for traffic analysis, and the binary K function for co-location analysis. Each of these extensions adapts several aspects of the spatial K function, which will have an impact on the corresponding computational flow and task complexity. The estimation and simulation of the spatio-temporal K function is described below.

2.4.2. Estimation and simulation of Ripley's K-function in space-time. In the spatio-temporal dimension, the aggregation mode of a point pattern is defined as simultaneous aggregation in the spatial and temporal dimensions, similarly, the discrete mode requires that the point pattern behaves discretely in the spatial and temporal dimensions at the same time, and cases other than this are considered spatio-temporal random. Similar to the spatial K-function, the spatio-temporal K-function mainly considers the density of points in the spatio-temporal dimension as well as the distances between pairs of points. The theoretical formulation of the spatio-temporal K function defines the spatio-temporal K value as the quotient of the expected total number of spatio-temporal points $E(s,t)$ within a spatial distance s and within a temporal distance and the density of spatio-temporal points λ_{st} as shown in Eq:

$$K(s,t)=\frac{E(s,t)}{\lambda_{st}} \tag{19}$$

$E(s,t)$ represents the expected value of the number of points in a cylinder centered at any point, s being the radius and $2t$ the height, while λ_{st} is obtained by dividing the total number of points by the volume of the cylinder. If $K(s,t)=\pi s^2 t$, it indicates that the observation points exhibit a complete spatio-temporal random distribution CSTR) over spatial distance s and temporal distance t. If $K(s,t)>\pi s^2 t$, it indicates that the expected number of points of the observation point at spatial distance s versus temporal distance t is higher than the point pattern consistent with CSTR, and thus it can be considered to exhibit an aggregated pattern. If the K value of the observation point is calculated $K(s,t)<\pi s^2 t$, it is considered to exhibit a discrete pattern. In practice, the K value of the point pattern can be calculated using Eq:

$$\hat{K}(s,t)=\frac{A\cdot D}{n^2}\sum_{i=1}^{n}\sum_{j\neq 0}\frac{I_{s,t}(d_{ij},u_{ij})}{\omega_{ij}v_{ij}} \tag{20}$$

where A represents the area of the study area, D represents the study time interval, n denotes the total number of points, d_{ij} refers to the spatial distance between point p_i and point p_j, u_{ij} refers to the temporal distance between point p_i and point p_j, and $I_s,t(d_{ij},u_{ij})$ describes the spatiotemporal point-pair filtering rule, s denotes the spatial distance threshold, and t denotes the temporal distance threshold, which can be described by Eq:

$$I_{s,t}(d_{ij},t_{ij})=\begin{cases}1, & (d_{ij}\leq s)\,and\,(u_{ij}\leq t)\\ 0, & otherwise\end{cases} \tag{21}$$

In addition, Eq. ω_{ij} denotes the boundary effect correction weights for the spatial dimension, while v_{ij} denotes the boundary effect correction weights for the temporal dimension where the spatial weights ω_{ij} have the same definitions as in the spatial K function, and the temporal weights v_{ij} follow the following: if the time interval centered at the moment of the point p_i, with a radius of u_{ij}, is completely encompassed by the time interval D of the study, then the temporal weights are set to 1, and otherwise to 1/2.

As shown in Eq. The spatio-temporal K function can also be converted to a spatio-temporal L function to facilitate a more intuitive comparison of the observation point pattern with CSTR. When the value of L is 0, it means that the generation process of the observation point conforms to CSTR, and when the value of L is greater than 0, it means that the observation point exhibits spatio-temporal aggregation pattern. When the value of L is less than 0, it indicates that the observation point exhibits a spatio-temporal discrete pattern.

$$\hat{L}(s,t)=\sqrt{\hat{K}(s,t)/\pi t}-s \tag{22}$$

3. Results and discussion

3.1. Evaluation and Analysis of Tianjin Fashion Industry Competitiveness

3.1.1. Entropy method for determining weights. The entropy value and weight of each evaluation indicator are shown in Table 2. The importance of the indicator to the evaluation object can be seen through the size of the weight, which takes the value range (0,1), the closer the value is to 1 indicating that the indicator is more important, and the fluctuation of the indicator has a greater influence on the evaluation results. From the table, it can be seen that the factors contributing most to the competitiveness of the fashion industry among the four dimensions of the first-level indicators are the related industries and governmental elements, with a weight of 0.2857, followed by the demand elements and resource elements, with weights of 0.2511 and 0.2363, respectively, and the factors contributing the least to the competitiveness are the elements of corporate strategy and competition in the same industry, with a weight of 0.2269.

In terms of resource elements: the number of students enrolled in general colleges and universities and whether or not there is a national Internet backbone direct connection point have a greater impact on the competitiveness of the fashion industry, with weights of 0.054 and 0.0505, respectively. Compared with other industries, the fashion industry has a longer product production cycle and a greater demand for various types of capital, such as production equipment and labor. Therefore, for Tianjin, improving the region's industrial infrastructure and increasing the level of scale can greatly enhance the competitiveness of its fashion industry. From the aspect of demand factors, the per capita consumption expenditure share of clothing is an important factor affecting the competitiveness of the fashion industry, with a weight of 0.0622. From the aspect of related industries and government factors, the transit visa-free policy is the main factor affecting the competitiveness of the fashion industry, with a weight of 0.0605. From the aspect of enterprise strategy and peer competition factors, the number of fashion enterprises has a higher degree of influence on the competitiveness of the fashion industry than the other three factors. For Tianjin, future cooperation and exchanges with more high-tech enterprises to improve the production, research and development and other technological levels of the enterprises will greatly contribute to the development of the fashion industry.

Table 2. The entropy and weight of each evaluation index

Primary indicator	Secondary indicator	Entropy	Secondary weight	Primary weight
X1	X11	0.8928	0.0477	0.2363
	X12	0.8829	0.054	
	X13	0.9033	0.0342	
	X14	0.8521	0.0467	
	X15	0.831	0.0505	
	X16	0.876	0.0032	
X2	X21	0.9262	0.0544	0.2511
	X22	0.8976	0.0302	
	X23	0.8616	0.0464	
	X24	0.8612	0.0622	
	X25	0.8924	0.0579	
X3	X31	0.9085	0.0581	0.2857
	X32	0.8768	0.0508	
	X33	0.898	0.0431	
	X34	0.9042	0.058	
	X35	0.8174	0.0605	
	X36	0.9067	0.0152	
X4	X41	0.9441	0.0385	0.2269
	X42	0.8864	0.0897	
	X43	0.8737	0.0536	
	X44	0.8747	0.0451	

3.1.2. TOPSIS evaluation results. On the basis of finding the weights, the competitiveness score of Tianjin fashion industry in 2020-2023 can be calculated through the formula, and the competitiveness score of Tianjin fashion industry is shown in Table 3. There are differences in competitiveness between the dimensions of Tianjin fashion industry, and the best performance in competitiveness is the demand element, which is kept around 0.59 on average, indicating that it is doing better in terms of per capita GDP, per capita disposable income, per capita consumption expenditure, per capita consumption expenditure share of clothing, and per capita consumption expenditure share of other goods and services in Tianjin fashion industry. From the comprehensive score situation, the comprehensive competitiveness level of Tianjin fashion industry is slowly increasing, and in the future, by continuously optimizing the industrial layout and giving full play to the characteristic advantageous industries, the competitiveness of Tianjin fashion industry will also be better realized.

Table 3. Tianjin fashion industry competitiveness score

	2020	2021	2022	2023
X1	0.032	0.0211	0.0171	0.0456
X2	0.5037	0.5865	0.5941	0.6666
X3	0.0123	0.016	0.02	0.0395
X4	0.0159	0.0181	0.0202	0.0471
Comprehensive score	0.2579	0.3002	0.3	0.3591

3.1.3. Comprehensive Competitiveness Comparison. With reference to the Tianjin fashion industry competitiveness evaluation index system, the data related to the competitiveness of China's fashion industry were collected, and due to the serious lack of data from Tibet, the data from 30 provinces in

China other than Tibet were finally collected, spanning the period from 2020 to 2023. The same entropy weight-TOPSIS method is used to evaluate it, and finally the fashion industry competitiveness score of each province in China is obtained, which shows what position the fashion industry of Tianjin City is in the scope of China. In view of the large number of evaluation objects, only the top 10 provinces plus Tianjin City with a total of 11 provinces and the average level of competitiveness of China's fashion industry are listed, and the comprehensive score of the competitiveness of China's top 10 provinces and Tianjin City's fashion industry is shown in Table 4. As can be seen from the table, the competitiveness of the fashion industry within China is not balanced among the provinces. In terms of region, the eastern region has the best fashion industry development, with Jiangsu, Shandong, Guangdong and Zhejiang provinces among the top five for four consecutive years. The central region accounts for four of the top 10, namely Anhui, Jiangxi, Henan and Hubei provinces. In the west, only Sichuan province broke into the top 10. Northeast China is a far cry from China, with no northeastern provinces in the top ten. According to the final results of the calculation of the national average level of competitiveness of the fashion industry, it is found that the competitiveness of the fashion industry in Tianjin is lower than the national average.

Table 4. The ranking of the top 10 provinces and tianjin fashionable industry competitiveness

	2020		2021		2022		2023	
Sort	Province	Score	Province	Score	Province	Score	Province	Score
1	Jiangsu	0.6194	Jiangsu	0.6719	Jiangsu	0.7572	Jiangsu	0.822
2	Shandong	0.5119	Guangdong	0.524	Guangdong	0.5855	Guangdong	0.6444
3	Guangdong	0.4847	Shandong	0.4701	Shandong	0.5479	Shandong	0.6021
4	Zhejiang	0.3764	Zhejiang	0.4155	Zhejiang	0.4769	Zhejiang	0.5185
5	Anhui	0.2545	Sichuan	0.2737	Sichuan	0.3071	Beijing	0.3416
6	Sichuan	0.2495	Anhui	0.2579	Anhui	0.2854	Sichuan	0.3311
7	Hupei	0.2328	Hupei	0.2406	Hupei	0.2804	Hupei	0.3061
8	Henan	0.2269	Jiangxi	0.2384	Jiangxi	0.2606	Anhui	0.2899
9	Jiangxi	0.216	Henan	0.2264	Henan	0.2466	Jiangxi	0.2764
10	Beijing	0.1933	Beijing	0.2121	Beijing	0.2336	Henan	0.2742
Tianjin	0.1198		0.1102		0.1195		0.1432	
Mean	0.1635		0.1745		0.1932		0.2236	

In order to more deeply analyze the reality of the competitiveness of the fashion industry in Tianjin and its strengths and weaknesses, based on the evaluation of the competitiveness of the fashion industry in 30 provinces in the country in 2020-2023, Jiangsu, Shandong and Guangdong Province, which have been ranked in the top three consecutively for four years, are selected as the target, and compared and analyzed in order to understand what problems exist in the process of development of the fashion industry in Tianjin and what to do in the future to solve the problems and gradually improve its strength. Gradually improve its own strength. Analyzing the fashion industry of Tianjin and the above three provinces in 2020-2023, the comprehensive score of fashion industry competitiveness changes as shown in Figure 1. As can be seen from the figure, the comprehensive score of the competitiveness of the fashion industry in Tianjin in 2020-2023 shows a slow rising trend, with a competitiveness score of 0.2895 in 2021, a year-on-year increase of 4.29% compared with 0.2466 in 2020, a competitiveness score of 0.2936 in 2022, an increase of 0.41% compared with the previous year, and a competitiveness score of 0.3451 in 2023, an increase of 5.15% compared with the previous year. 5.15% increase over the previous year, which shows that although there is a general trend of growth, the growth is unstable.

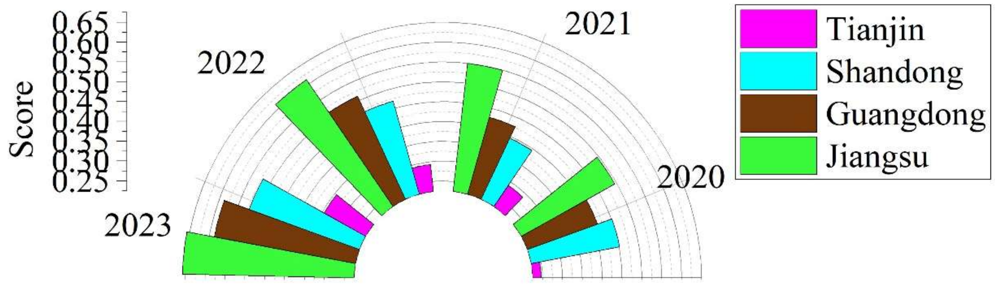


Fig. 1. Comprehensive scoring of fashion industry competitiveness

3.2. Characterization of spatial distribution of fashion industry in Tianjin

3.2.1. Quantitative statistics on the distribution of the fashion industry. According to the summary of the classification research on fashion industry, following the evolution mechanism within the industry, and in connection with the characteristics of the development of Tianjin's fashion industry, this paper divides the fashion industry into three circles: the core layer, the expansion layer and the extension layer. On the basis of this classification, through the statistics and comparison of the number of POIs in different circles of the fashion industry in each district of Tianjin, it is not difficult to find that the distribution of the number of districts is seriously unbalanced, and the distribution of the number of different circles in the same area also has significant differences, the total number of districts and the number of each circle of the fashion industry in Tianjin is shown in Table 5. From a general point of view, in the fashion industry data of each district, the proportion of the number of core layers is much higher than the number of extension layers, and the number of extension layers in each district is not much different, of which the highest proportion of core layers is in the Binhai New Area, and the highest proportion of extension layers is in the Hebei District and the Ninghe District. Locally, the total number of fashion industries in districts such as Hexi District and Hebei District are more widely distributed, and the core layer accounts for a larger proportion, forming an incipient women's clothing block functional area, which is mainly a processing cluster for garments and apparel products. The next largest number is in old urban areas such as Hongqiao District. All in all, the fashion industry in Tianjin has formed a development pattern dominated by the new urban areas and supplemented by the old urban areas and the surrounding belts of the neighboring urban areas.

Table 5. The total number of districts in the fashion industry and the number

Area Name	Total	Core Layer		Extended Layer		Extension Layer	
		Quantity	Proportion	Quantity	Proportion	Quantity	Proportion
Peace Zone	1442	827	6.49%	319	7.43%	296	5.47%
East Side	541	317	2.49%	35	0.82%	189	3.49%
West Side	2369	1885	14.79%	216	5.03%	268	4.95%
South Opening	949	502	3.94%	178	4.15%	269	4.97%
River North	3198	1754	13.77%	613	14.28%	831	15.35%
Red Bridge	1317	818	6.42%	274	6.38%	225	4.16%
Binhai New Area	3419	2193	17.21%	472	11.00%	754	13.93%
Southeast Asia	1230	828	6.50%	174	4.05%	228	4.21%
Qinghai	1547	763	5.99%	411	9.58%	373	6.89%
South	1232	795	6.24%	199	4.64%	238	4.40%
Beichen District	1402	632	4.96%	364	8.48%	406	7.50%
Wuqing District	534	284	2.23%	83	1.93%	167	3.09%
Baodi District	669	328	2.57%	154	3.59%	187	3.45%
Ninghe	1339	263	2.06%	203	4.73%	873	16.13%
Static Sea Area	510	188	1.48%	312	7.27%	10	0.18%
Thistle	748	364	2.86%	285	6.64%	99	1.83%

Combining the land area and population density of each area, the land area and the total number of fashion industries in each district of Tianjin are shown in Table 6. The relatively densely populated Heping District, Hedong District and Hexi District of Tianjin also have a higher density of fashion industry distribution, all of which are at more than 10 places/km^2, with the highest industry density and also the highest population density of Heping District, with an industry density of up to 84.5 places/km^2, while the distribution density of the fashion industry in the less densely populated areas such as Jinghai District and JiZhou District is also smaller, at 0.1-0.8 places/km^2, below 1 place/km^2, and the degree of aggregation is not as significant as that of other areas. km^2, lower than 1 place/km^2, and the degree of aggregation is not as significant as other areas. In summary, the distribution density of fashion industry and population distribution density in Tianjin are highly fitted in trend, and the distribution number of fashion industry in Tianjin is positively correlated with the population distribution density in general within a certain range. Therefore, population density influences the degree of aggregation of fashion industry in the region within a certain range.

Table 6. Total land area and fashion industry total in Tianjin

Area Name	Total	Land area(km^2)	Industrial density(area·km-2)	Population density(person/km-2)
Peace Zone	2401	23	84.4822362	14595
East Side	516	32	20.88528152	12263
West Side	1234	66	17.72743261	5755
South Opening	926	87	12.67923084	3853
River North	1333	198	5.68036366	3194
Red Bridge	1477	310	5.15192122	2474
Binhai New Area	3402	1230	2.61909065	937
Southeast Asia	3215	1415	2.55502022	968
Qinghai	1530	1819	1.25342033	377
South	1352	2312	1.58944361	216
Beichen District	1229	3120	0.41826487	172
Wuqing District	648	1828	0.05242502	247
Baodi District	485	4416	0.52909639	106
Ninghe	865	3002	0.3261115	84
Static Sea Area	456	1263	0.2519463	112
Thistle	244	1065	0.3656412	95

3.2.2. Circle structure analysis. In order to further visualize the distribution of different circle structures in the city center area and the degree of coupling of city circle structures, the circle structure of the distribution of fashion industry facilities in Tianjin is studied by using the method of radius of gyration analysis. The statistics of the number of each fashion industry circle in Tianjin Caixiao District are shown in Table 7. The distribution of fashion industry facilities is mainly concentrated in 0~20km, and the highest density area is 0~10km at the center circle, the whole shows a pattern of multi-point radiation around the center, and as the center circle transitions to the periphery, the number of fashion industry facilities also shows a gradually decreasing trend. In terms of density, the peak of the core layer is at 0-10 km, which is located in the center circle of the city and has a strong industrial base. On the other hand, the peaks of the expansion layer and the extension layer are at 10 to 20 km, in the immediate neighborhood circle, and these two categories mainly realize the transformation of benefits through the provision of high-technology services, and thus are mainly concentrated in the Heping District, which has been rapidly developing and constructing in recent years. Although geographic location and the degree of economic development have a significant impact on the expansion and extension layers of the fashion industry, the requirements for urban locations are relatively low compared with those of the core layer. In terms of trend, the distribution trend of the number of each circle in the core layer is significantly different from that of the extension and expansion layers, with an overall trend of rapid decline. On the other hand, the distribution number of the other two types of facilities has a small increase at 10-20km and a steady decline after 10-20km, with relatively smooth changes overall, while the number of all three types of facilities reaches a minimum value at 40-50km and tends to be the same.

Table 7. Statistics on the number of various fashion industries in tianjin jiangang district

Distance/km	Core layer	Extended layer	Extension layer
0~10	3917	811	1015

10~20	2819	806	1101
20~30	1444	402	564
30~40	804	173	309
40~50	122	102	78

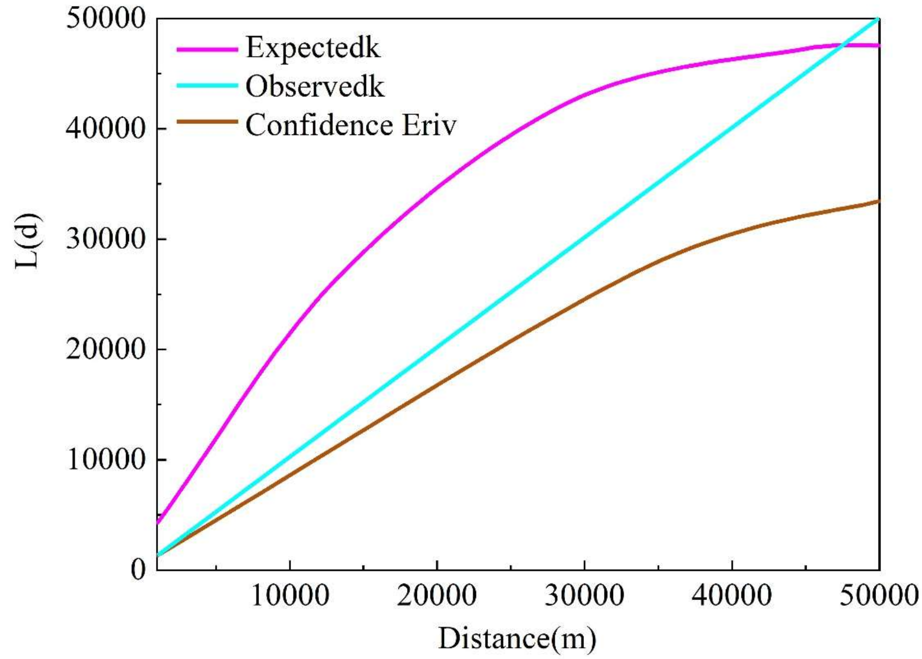
3.3. Characterization of Tianjin Fashion Industry Agglomeration and Most Significant Dimensions

3.3.1. Level of agglomeration based on the spatial Gini coefficient. The measurement results of the spatial Gini coefficient of strategic fashion industry in Tianjin are shown in Table 8. As can be seen from the results, the spatial Gini value of digital and fashion reaches 0.236, with the most significant degree of agglomeration, followed by new generation electronic information and high-end manufacturing equipment, with the results of 0.084 and 0.063 respectively. The second is the new generation of electronic information and high-end manufacturing equipment, the results are 0.084 and 0.063 respectively, through the measured data can be found, the spatial Gini coefficient of the agglomeration degree of the results of the measurement and the kernel density analysis of the conclusions of the new generation of electronic information industry, high-end manufacturing equipment industry, the green and low-carbon industry presents the characteristics of the point distribution, it is difficult to scale up into a piece of agglomeration, so its spatial Gini coefficient value of the results of the measurement is 0.236, the degree of agglomeration is most significant. The result of Gini coefficient calculation does not have a large value, while the digital and fashion industry can continue to agglomerate and develop in the area with a certain scale of development in the early stage, and the industry forms the form of piecemeal development, so its spatial Gini coefficient calculation is higher than that of the new generation of electronic information industry, high-end manufacturing equipment industry, and the green and low-carbon industry, and the degree of agglomeration is more significant.

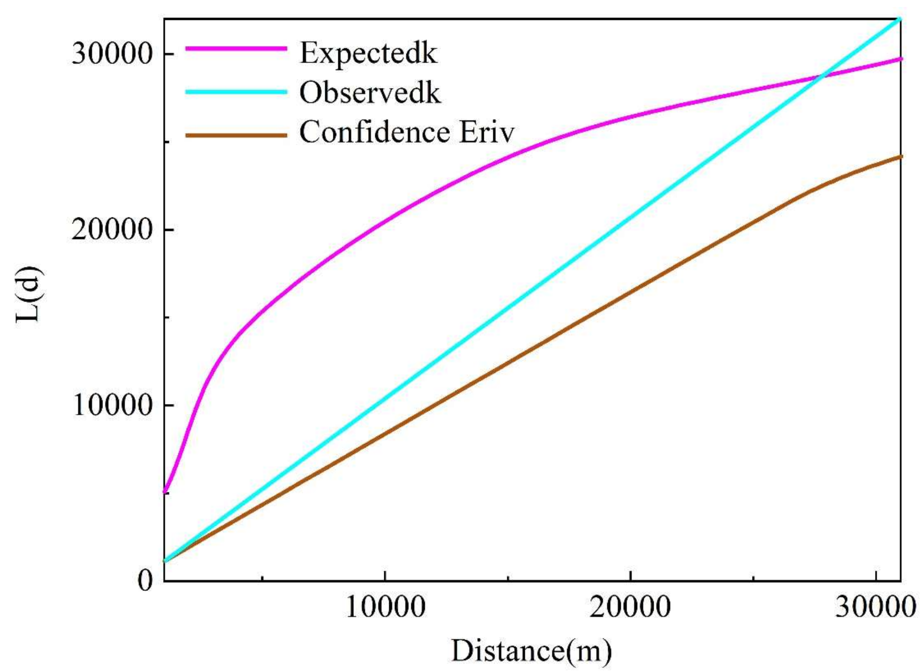
Table 8. The calculation results of the strategic emerging industrial space gini coefficient

	New generation of electronic information	Digital and fashion	High-end manufacturing equipment	Green low-carbon	New material
Peace Zone	0.001	0.003	0.004	0.002	0.005
East Side	0.001	0.000	0.000	0.000	0.000
West Side	0.023	0.045	0.023	0.017	0.007
South Opening	0.000	0.000	0.001	0.000	0.000
River North	0.03	0.025	0.001	0.006	0.005
Red Bridge	0.000	0.002	0.000	0.005	0.005
Binhai New Area	0.001	0.001	0.001	0.003	0.003
Southeast Asia	0.001	0.000	0.000	0.000	0.008
Qinghai	0.000	0.000	0.000	0.000	0.000
South	0.003	0.000	0.001	0.000	0.000
Beichen District	0.004	0.002	0.004	0.004	0.004
Wuqing District	0.002	0.000	0.000	0.000	0.003
Baodi District	0.006	0.068	0.026	0.01	0.008
Ninghe	0.001	0.000	0.002	0.001	0.003
Static Sea Area	0.007	0.067	0	0.003	0.004
Thistle	0.004	0.023	0.000	0.004	0.004
Total	0.084	0.236	0.063	0.055	0.059

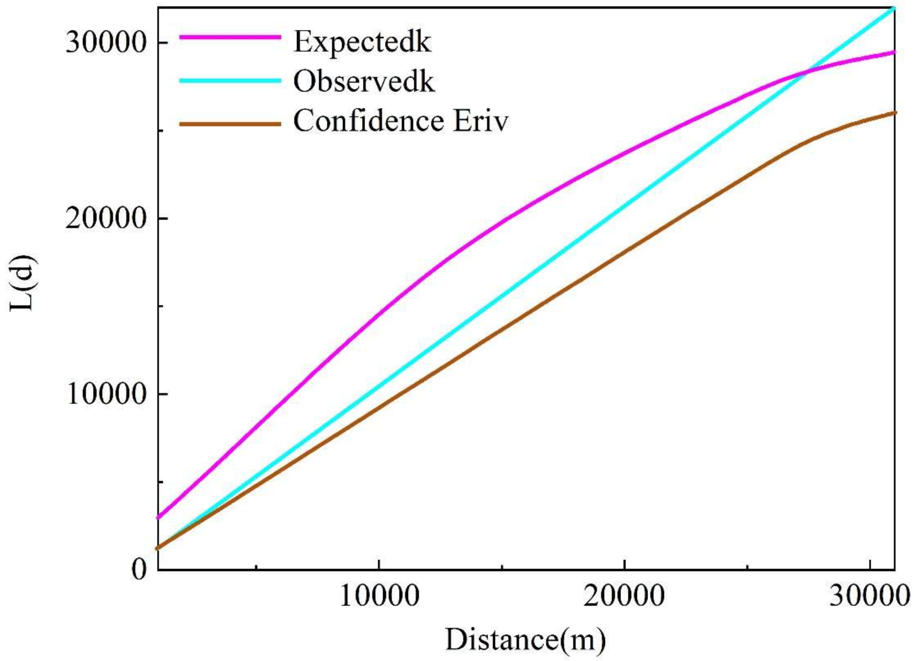
3.3.2. Clustering scales based on Ripley's K-function. Spatial cluster analysis is an important tool for exploring spatial patterns and identifying areas of high concentration of specific phenomena. In this study, the spatial concentration scales of five strategic fashion industries in Tianjin were analyzed using ArcGIS 10.6 software. The results of this analysis help to identify the scales at which certain industries are concentrated and provide decision makers with information on how to develop and support these industries. The analysis shows that the new generation of electronic information technology is the most widely distributed industry in space, with the most significant scale of concentration reaching 21,000 m and a DiffK value of 13,365.285. This indicates that this industry has a wide range of distribution and a high density of firms, and that it is a key industry in Tianjin's strategic fashion industries. Interestingly, high-end manufacturing equipment, green low-carbon, and new materials industries have similar most significant agglomeration scales and similar DiffK values. The most significant agglomeration scales of these industries are in the range of 5 to 10 kilometers, indicating that they have a relatively concentrated distribution pattern in a certain area. Policy makers can use this information to support these industries and encourage cluster development to promote economic growth. Overall, multi-scale spatial cluster analysis is a powerful tool for understanding the scale of industrial agglomeration in a region, and can provide a valuable basis for policymakers to formulate targeted policies and support the development of the fashion industry.The statistics of Ripley's K-function model are shown in Fig. 2 (a~e are denoted as new-generation electronic information, digital and fashion, high-end manufacturing equipment, respectively, (green low-carbon and new materials).



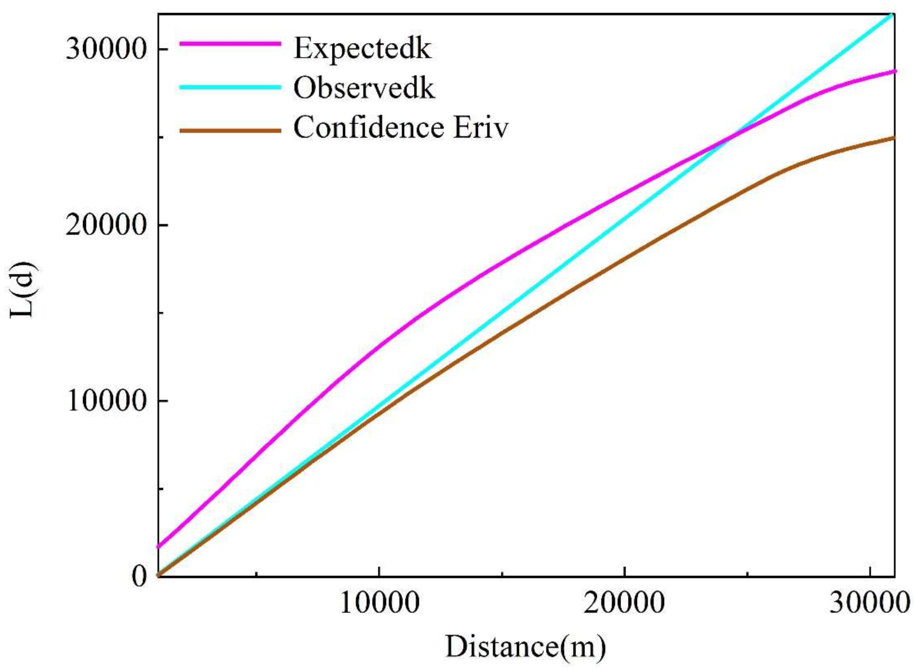
(a) New generation of electronic information



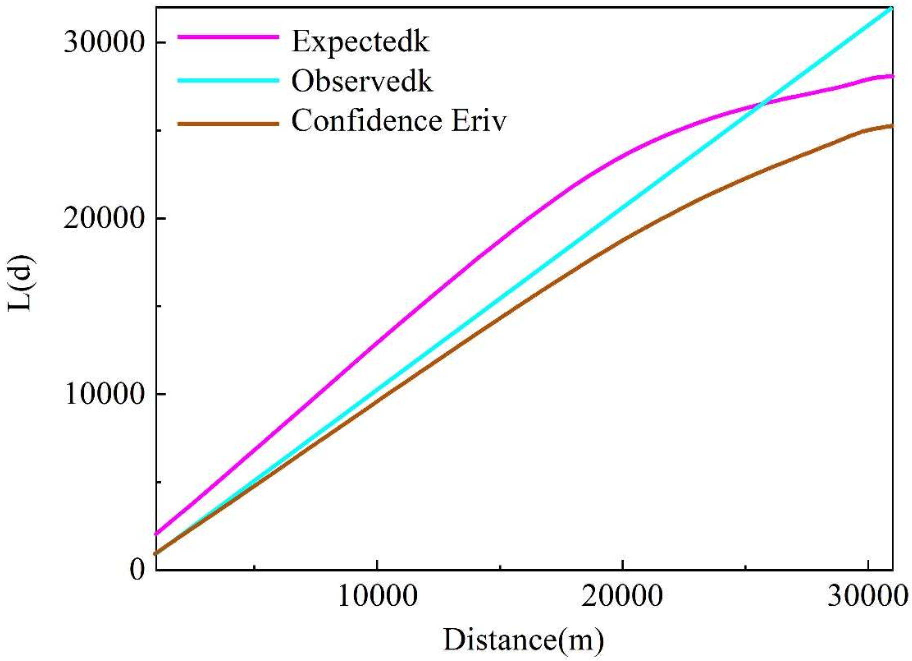
(b) Digital and fashion



(c) High-end manufacturing equipment



(d) Green low-carbon



(e) New material

Fig. 2. The ripleys k function model statistics

1) New Generation Electronic Information. The statistics of Ripley's K(d) index for new generation electronic information technology is shown in Table 9. From the table, it can be seen that the observed values of the new generation of electronic information industry in the range of 0.1 to 4.6 kilometers are always above the expected and observed values. This result indicates that in this range, the new generation of electronic information technology is always in the state of significant agglomeration, and the spatial scope of agglomeration changes from large to small. The most significant agglomeration scale is about 22,000 meters, and the DiffK value corresponding to the most significant agglomeration scale is 13317.938.

Table 9. The new generation of electronic information technology, ripleys k(d) index statistics

OBJECTID	Expecte dK	Observe dK	DiffK	Lw ConfEnv	Hi ConfEnv
1	1000	3803.231	2752.379	977.183	1018.675
2	5000	11897.676	6899.121	4831.321	4868.399
3	12000	20158.193	10142.923	9263.629	9469.304
4	16000	27182.203	12188.569	13332.069	13718.403
5	18000	31074.222	13049.194	15647.525	16085.88
6	22000	33314.189	13317.938	17127.566	17594.281
7	24000	34313.533	13284.167	17831.919	18319.116
8	28000	38202.943	13206.711	20599.005	21165.529
9	32000	41715.483	11654.172	23698.164	24321.898
10	35000	43735.721	8710.617	26578.273	27098.544
11	42000	44953.277	4973.442	28980.347	29463.868
12	45000	45915.893	895.0435	30933.905	31473.938
13	52000	46687.792	-3259.725	32617.821	33265.251

2) Numbers and Fashion. The statistics of Digital & Fashion Ripley's K(d) index is shown in Table 10. From the table, it can be seen that the observed value of the digital and fashion industry in the range of 0.1 to 2.5 kilometers is always located above the expected value and the observed value, and this

result indicates that in this range, the digital and fashion is always in the state of significant agglomeration, and the spatial range of agglomeration is changing from large to small. The most significant clustering scale is about 7000 meters, and the DiffK value corresponding to the most significant clustering scale is 8812.466.

Table 10. Figures and fashion ripleys k(d) index statistics

OBJECTID	Expecte dK	Observe dK	DiffK	Lw ConfEnv	Hi ConfEnv
1	1000	5096.359	4097.72	969.298	1004.472
2	5000	13423.016	8439.219	4787.571	4876.508
3	6000	14696.497	8708.775	5671.761	5803.055
4	7000	15810.317	8812.466	6585.395	6709.482
5	8000	16599.133	8603.658	7446.23	7565.923
6	9000	18166.267	8159.822	9152.587	9299.696
7	12000	21432.279	6405.298	13134.696	13393.061
8	20000	24389.889	4365.631	16721.236	17125.69
9	22000	27274.337	2292.714	19855.721	20393.88
10	32000	29204.207	-798.1288	22653.84	23208.671
14	35000	30671.55	-4345.92	25067.246	25609.623

3) High-end manufacturing equipment. The statistics of Ripley's K(d) index for high-end manufacturing equipment are shown in Table 11, where the observed values of the high-end manufacturing equipment industry in the range of 0.1 to 2.5 kilometers are consistently above the expected and observed values. This result indicates that within this range, high-end manufacturing equipment is always in a state of significant agglomeration, and the spatial range of agglomeration changes from large to small. The most significant agglomeration scale is about 10,000 meters, and the DiffK value corresponding to the most significant agglomeration scale is 3497.29, which is a small difference.

Table 11. High end manufacturing equipment ripleys k(d) index statistics

OBJECTID	Expecte dK	Observe dK	DiffK	Lw ConfEnv	Hi ConfEnv
1	1000	2499.99	1520.101	911.877	1069.541
2	7000	7935.975	2945.367	4691.448	4940.563
3	9000	12372.185	3447.869	8185.883	8478.437
4	10000	13486.913	3497.29	9016.358	9395.113
5	12000	14437.475	3447.445	9835.84	10208.011
6	18000	17891.502	2869.066	12963.934	13413.127
7	22000	21858.054	1883.025	16459.611	17155.18
9	32000	27587.742	-2373.005	22288.965	23097.954

4) Green Low Carbon. The statistics of green low carbon Ripley's K(d) index is shown in Table 12. From the table, it can be seen that the observed values of green low-carbon industries in the range of 0.1 to 2.4 km are always above the expected values. This result indicates that in this range, the green low-carbon industry is always in the state of significant agglomeration, and the spatial extent scale of agglomeration changes from large to small. The most significant agglomeration scale is about 12,000 meters, and the DiffK value corresponding to the most significant agglomeration scale is 2838.371, and the DiffK difference is not large compared with the other types of industries.

Table 12. Green and low carbon ripleys k(d) index statistics

OBJECTID	Expecte dK	Observe dK	DiffK	Lw ConfEnv	Hi ConfEnv

1	1000	2132.145	1109.993	897.643	1067.68
2	7000	7590.204	2553.651	4709.383	4921.833
3	9000	11778.699	2800.218	8223.736	8473.731
4	10000	12830.735	2834.687	9062.638	9358.715
5	12000	13831.326	2838.371	9878.853	10308.285
6	15000	17411.071	2435.547	12996.011	13580.839
7	22000	21196.671	1241.869	16545.089	17238.787
8	25000	24705.623	-295.245	19740.635	20503.777
9	32000	27363.998	-2659.534	22578.374	23383.38
10	35000	29083.185	-5917.85	24965.819	25759.935

5) New materials. The statistics of Ripley's K(d) index for new materials are shown in Table 13. From the table, it can be seen that the observed values of green and low-carbon industries in the range of 0.1 to 2.0 km are always above the expected values. This result indicates that in this range, the new material industry is always in the state of significant agglomeration, and the spatial range of agglomeration changes from large to small. The most significant agglomeration scale is about 10,000 meters, and the DiffK value corresponding to the most significant agglomeration scale is 2904.483, which is not a big difference compared with other types of industries.

Table 13. New material ripleys k(d) index statistics

OBJECTID	Expecte dK	Observe dK	DiffK	Lw ConfEnv	Hi ConfEnv
1	1000	2133.31	1147.271	888.912	1048.149
2	7000	7577.377	2543.431	4677.313	4888.832
3	9000	11847.095	2856.702	8206.875	8514.946
4	10000	12891.859	2904.483	9015.638	9357.017
5	12000	13808.656	2777.945	9839.772	10263.246
7	18000	20388.511	336.536	16379.028	17154.485
9	30000	25176.956	-4856.922	21995.162	23074.827
10	35000	26625.218	-8360.388	24238.838	25414.694

6) Summary. In general, the statistics of the most significant agglomeration scales of various strategic emerging industries are shown in Table 14, and the most significant agglomeration scales of most of the industries are within the interval of 5,000 to 10,000 meters, and the most significant agglomeration scale of the new generation of electronic information technology industry is the largest and reaches 22,000 meters, and its DiffK value is also the highest and reaches 13,317.938, which indicates that new generation of electronic information industry As a leading industry in the category of strategic fashion industry in Tianjin, it has a wide range of distribution and a large and dense number of enterprises.

Table 14. The most significant accumulation scale statistics

OBJECTID	Categories	Maximum concentration scale(m)	Diffk value
1	New generation of electronic information	22000	13317.938
2	Digital and fashion	7000	8812.466
3	High-end manufacturing equipment	10000	3497.29
4	Green low-carbon	12000	2838.371
5	New material	10000	2904.483

4. Conclusion

As a high value-added industry integrating advanced manufacturing and modern service industry, fashion industry is an important force driving economic development in the future, and it is of great significance to the construction of international consumption center city. The article constructs a set of data analysis system of Tianjin fashion industry from the competitiveness, spatial distribution characteristics and industrial agglomeration of Tianjin fashion industry. The research conclusions are as follows:

By evaluating the competitiveness of Tianjin's fashion industry in 2020-2023, it is finally found that its competitiveness level is slowly increasing during the 4-year period, but the industrial development is not balanced compared with provinces such as Jiangsu, Shandong and Guangdong, etc. Tianjin's fashion industry suffers from the problems of low scale level, low market share, insufficient innovation impetus, and low R&D output.

By calculating the level of agglomeration and the range of the most significant agglomeration scale of various types of fashion industries in Tianjin, it is shown that the spatial distribution characteristics and agglomeration degree of different types of strategic emerging industries are different, and the most significant agglomeration scales of most of the industries are concentrated in the range of 5km to 10km, while that of the new-generation electronics and information technology industry has the largest most significant agglomeration scale of 22,000 meters, with the DiffK value of 13,317.938. 13317.938.

In order to improve the competitiveness of Tianjin fashion industry, the government should continue to strengthen the level of fashion industry agglomeration and improve the coordinated development of the region. Optimize the investment environment of fashion industry and increase government support. Deepen the mutual integration of industries with the help of inherent characteristic resources. Enterprises need to increase investment in scientific research, improve R & D innovation capacity. Carry out specialized cooperation to improve the level of production technology. Establish fashion brand advantages and expand market share.

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References

[1] Rathore, B. (2021). Fashion Transformation 4.0: Beyond Digitalization & Marketing in Fashion Industry. Eduzone: International Peer Reviewed/Refereed Multidisciplinary Journal, 10(2), 54-59.

[2] Sudha, M., & Sheena, K. (2017). Impact of influencers in consumer decision process: the fashion industry. SCMS Journal of Indian Management, 14(3), 14-30.

[3] Rathnayaka, U. (2018). Role of digital marketing in retail fashion industry: A synthesis of the theory and the practice. Journal of Accounting & Marketing, 7(02).

[4] Gandhi, S. (2020). Analysis of impulsive buying behavior in fashion industry. International Journal of Engineering and Management Research, 10.

[5] Scuotto, V., Del Giudice, M., Della Peruta, M. R., & Tarba, S. (2017). The performance implications of leveraging internal innovation through social media networks: An empirical verification of the smart fashion industry. Technological Forecasting and Social Change, 120, 184-194.

[6] Kim, C. E., & Lee, J. H. (2018). Trends of big data and artificial intelligence in the fashion industry. Journal of the Korean Society of Clothing and Textiles, 42(1), 148-158.

[7] Lyu, Y., & Lv, X. (2022). The Cutting-Edge Applications and Trends of Big Data and AI Technology in the Digitalization of the Fashion Industry. In 2021 International Conference on Big Data Analytics for Cyber-Physical System in Smart City: Volume 1 (pp. 1073-1081). Springer Singapore.

[8] Poorthuis, A., Power, D., & Zook, M. (2020). Attentional social media: Mapping the spaces and networks of the fashion industry. Annals of the American Association of Geographers, 110(4), 941-966.

[9] Yang, S., Song, Y., & Tong, S. (2017). Sustainable retailing in the fashion industry: A systematic literature review. Sustainability, 9(7), 1266.

[10] Ponis, S. T., & Lada, C. (2021). Digital transformation in the Greek fashion industry: A survey. International Journal of Fashion Design, Technology and Education, 14(2), 162-172.

[11] Mok, A., Yu, H., & Zihayat, M. (2022). The trends of sustainability in the luxury fashion industry: A Triple Bottom Line analysis. Journal of global fashion marketing, 13(4), 360-379.

[12] Madhura, K., & Panakaje, N. (2022). Social Media as a Promotional Tool in the Fashion Industry: A Case Study on Meta Platforms Inc. International Journal of Case Studies in Business, IT and Education (IJCSBE), 6(1), 351-365.

[13] Oliveira, R. C., de Alencar Näas, I., & Garcia, S. (2022). Fashion Industry 4.0: A Bibliometric Review in the Fashion Industry. Research, Society and Development, 11(12), e490111234203-e490111234203.

[14] Garcia, C. C. (2022). Fashion forecasting: an overview from material culture to industry. Journal of Fashion Marketing and Management: An International Journal, 26(3), 436-451.

[15] Song, E. Y., & Lim, H. S. (2021). Perceptions and trends of digital fashion technology-A big data analysis. Fashion & Textile Research Journal, 23(3), 380-389.

[16] Rudniy, A., Rudna, O., & Park, A. (2024). Trend tracking tools for the fashion industry: the impact of social media. Journal of Fashion Marketing and Management: An International Journal, 28(3), 503-524.

[17] Lee, S. E., Ju, N., & Lee, K. H. (2021). Visioning the future of smart fashion factories based on media big data analysis. Applied Sciences, 11(16), 7549.

[18] Younus, M., Hossen, S., & Islam, M. M. (2024). Advanced Business Analytics In Textile & Fashion Industries: Driving Innovation And Sustainable Growth. International Journal of Management Information Systems and Data Science, 1(2), 37-47.

[19] Bertola, P., & Teunissen, J. (2018). Fashion 4.0. Innovating fashion industry through digital transformation. Research journal of textile and apparel, 22(4), 352-369.

[20] Kim, E., Fiore, A. M., Payne, A., & Kim, H. (2021). Fashion trends: Analysis and forecasting. Bloomsbury Publishing.

[21] Esteban-Santos, L., García Medina, I., Carey, L., & Bellido-Pérez, E. (2018). Fashion bloggers: communication tools for the fashion industry. Journal of Fashion Marketing and Management: An International Journal, 22(3), 420-437.

[22] Liu, M. (2022). Determining the role of influencers' marketing initiatives on fast fashion industry sustainability: The mediating role of purchase intention. Frontiers in Psychology, 13, 940649.

[23] Casadei, P., & Lee, N. (2020). Global cities, creative industries and their representation on social media: A micro-data analysis of Twitter data on the fashion industry. Environment and Planning A: Economy and Space, 52(6), 1195-1220.

[24] Song, E. Y. (2021). A study on the perception of fashion platforms and fashion smart factories using big data analysis. Fashion & Textile Research Journal, 23(6), 799-809.

[25] Fani, V., Antomarioni, S., Bandinelli, R., & Ciarapica, F. E. (2023). Data mining and augmented reality: an application to the fashion industry. Applied Sciences, 13(4), 2317.

[26] Acharya, A., Singh, S. K., Pereira, V., & Singh, P. (2018). Big data, knowledge co-creation and decision making in fashion industry. International Journal of Information Management, 42, 90-101.

[27] Al-Obeidat, F., Hani, A. B., Benkhelifa, E., Adedugbe, O., & Majdalawieh, M. (2019, October). A sentiment analysis approach of data volatility for consumer satisfaction in the fashion industry. In 2019 Sixth International Conference on Social Networks Analysis, Management and Security (SNAMS) (pp. 262-267). IEEE.

[28] Chan, C. O., Lau, H. C., & Fan, Y. (2018, May). IoT data acquisition in fashion retail application: Fuzzy logic approach. In 2018 International Conference on Artificial Intelligence and Big Data (ICAIBD) (pp. 52-56). IEEE.

[29] Singhal, V., B Singh, A., Ahuja, V., & Gera, R. (2023). Consumer segmentation in the fashion industry using social media: An empirical analysis. Journal of Information and Organizational Sciences, 47(2), 401-421.

[30] Hongyu Zhu & Liang Mao. (2024). Research on Financial Performance Evaluation of Xiaoxiong Electric Appliance Based on Entropy Weight -TOPSIS Method. Academic Journal of Management and Social Sciences(1),125-133.

[31] Qi Zhang,Zhihong Lu,Shanshan Jing,Dong Guo & Lijun Wang. (2024). Comprehensive evaluation of the implementation of close-type county medical alliance in Shandong Province using entropy weight TOPSIS method and non-integer rank sum ratio method. BMC Health Services Research(1),1193-1193.

[32] Quanfu Yu & Jun Xu. (2025). Distribution reconstruction and reliability assessment of complex LSFs via an adaptive Non-parametric Density Estimation Method. Reliability Engineering and System Safety(PB),110609-110609.