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Exploring the Built Environment Factors Influencing Town Image Using Social Media Data and Deep Learning Methods

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Abstract: The representational image of the city has attracted people's long-term attention. Nevertheless, the mechanism of interaction between the image and the built environment (BE) and image studies at the town scale have not been fully explored. In this study, we collected multi-source data from 26 characteristic towns in Tianjin, China. We explored a deep learning approach to recognize social media data, which led to the development of quantifiable town uniqueness image (UI) variables. We studied the influence of the BE on the town UI and the moderating effects of positive emotions on the relationship between the two. The results showed that positive emotions had significantly positive moderating effects on the water system ratio's effect on UI, but weakened sidewalk density and tourist attraction density. They also inhibited the negative effects of road connectivity but could strengthen the negative effects of the sky view factor and points of interest (POI) mix. The moderating effects on other variables are relatively mediocre. This study helps to reveal the inner mechanism of BE and town image. It is conducive to accurately coordinating the relationship between planning policies and design strategies, optimizing resource allocation, and promoting sustainable town development.

Keywords: town uniqueness image; built environment; positive emotions; moderating effects; Tianjin

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1. Introduction

Since the 1990s, China's rapid urbanization process has been influenced by structural functionalism, and cities have lost their urban characteristics while gaining new faces [1], and are facing the problem of the retreat of city image [2]. Lynch divides city image into "path", "node", "edge", "district", and "landmark". He believes that after people perceive the BE, combined with subjective emotions, the memory and impression formed by the brain synthesis focus on the process of interaction between the BE and people's consciousness.

In recent years, urban–rural integration and rural revitalization have become important trends in social and economic development in developed and developing countries [3], which can enable the interactive flow of factors and the common development of urban and rural areas [4]. However, as of 2020, the urban–rural income ratio of developed countries such as the United Kingdom and Canada was close to 1, and African countries such as Uganda were only at about 2.3, while China was as high as 2.56 [5]. This shows that there is a big difference between urban and rural development in our country, with the countryside lagging far behind the cities. In the settlement system, towns not only belong to the rural areas but also play a vital role in connecting development as a link between the city and the countryside. Related studies have found that residents of towns are generally happier than those who live in cities [6]. During the COVID-19 epidemic, the characteristics of reverse urbanization of migration to non-metropolitan towns and rural areas was shown [7,8]. Evidence shows that exposure to the natural environment in towns improves mental and physical health [9]. However, due to the lack of infrastructure and resources in the town [10], as well as the inappropriate location, it is overlooked.

Currently, most research on images focuses on the urban scale and lacks an exploration of images in town spaces. By studying images at the town scale, exploring the mechanisms and factors that influence image production can provide people with a sense of security, belonging, and direction about the town [11]. In addition, scholars still focus on the holistic representation of the image, and no methodology provides a set of tools to quantitatively derive the intrinsic correlation mechanism between the image and the BE. BE in this paper refers to human-built or naturally occurring environments that are accessible and perceptible. This study attempts to explore the association between town image and objectified BE to enhance image performance from a human-centered perspective. It provides suggestions for relevant government agencies and planners to enable them to make precise policy decisions by designing and updating the BE factors that significantly affect the town image.

2. Literature Review

2.1. Town Image

An image is a collection of beliefs, thoughts, and impressions that a person holds about an object [12]. People's attitudes, emotions, and behavior are largely determined by the destination [13]. As stated in the stimulus organism response (S-O-R) model originating from the field of psychology, all aspects of the BE act as stimuli (S) to interfere with the internal emotional state (O) generated by individuals and drive their subsequent behavioral responses (R) [14]. This is a mixture of physical and social values, and a good image can increase attractiveness, uniqueness, and identity [11].

Regarding the city level, "The Image of the City" by Kevin Lynch is a landmark theory of lasting impact [15], widely used in the fields of urban planning, social science, and environmental psychology [16]. However, the scientific rigor of the city image theory is controversial. With the rise in postmodernism, many scholars have realized that socio-economic factors such as "social consciousness, cultural customs, history, and urban functions" should not be ignored in city image [17]. Relevant scholars argue that Lynch's theory has not been tested much in practice and that a large number of follow-up studies have only regarded Lynch's claim as a given theory [18]. For example, some scholars took the central area of Boston as a case, compared the results with Lynch's map, and found considerable differences in landmarks. Still, the correspondence between the other four elements is relatively good [19].

Towns are also regarded as human settlements, and can even be regarded as small cities, but they have received little attention before [20,21]. With the dominance of small cities poised to lead future urbanization across the globe, it is important to examine town-level image. For instance, in 2018, approximately 26.5% of the world's inhabitants lived in cities with fewer than 0.5 million inhabitants [22]. Similarly, the number of cities with a population of 0.5 million or more is projected to increase by 23% in Asia and 57% in Africa from 2018 to 2030 [23]. This situation can lead to rapid urban sprawl and town building.

Since 2016, relevant government departments in China have begun to construct characteristic towns nationwide. Yet, there are some problems in the construction of characteristic towns, such as disorderly spatial expansion and imperfect supporting facilities, especially the lack of characteristics, which do not meet the original expectations. Compared with cities, towns have a closer relationship with people. The research on town image can help understand the factors that significantly affect town characteristics from bottom to top and grasp the direction for future town construction and renewal.

2.2. Image and BE

The BE contains the material elements and spatial mental state in a human settlement, which can meet people's physiological and psychological needs and directly affect people's emotional state [24]. Most studies have shown that the degree of BE attributes would have a positive or negative effect on people's emotions through their effects on physical activity and social interaction [25,26]. Some data showed that people's image of a destination is determined by both cognition and emotion [27]. However, emotional responses were different from cognitive responses, although related. Emotions were formed based on cognition [28]. Most studies have found that cognition, as the precursor of the emotional component produced after people's perception [29,30], was the interaction state in the process of interaction between the individual and the environment [31]. Thus, the image refers to the result of geospatial consciousness, while cognition and emotion emphasize the process of image formation.

Regarding the cognition and evaluation of the image, Lynch mainly used cognitive map surveys [19], and later developed into questionnaire surveys [32], spatial syntax [33], and so on. The emergence of digital technology in the information age is both a threat and an opportunity for image research, making contemporary tourists active in acquiring destination images rather than showing passive acceptance [34]. Relevant scholars have gradually adopted multi-source big data and artificial intelligence technology, such as OSM [35], deep learning [36], and social media [5], to study human behavior, emotions, and perceptions of the urban environment. Compared with traditional sociological methods such as cognitive maps and questionnaires, social media is a low-cost, public, and high-coverage image perception method. For instance, Bertrand used Twitter data to analyze user behavior and sentiment tone in New York [37]. Liu et al. used deep learning to classify Flickr pictures and then performed statistical analysis on the images of seven typical cities around the world to explore the relevance and diversity of images [38]. Also, texts from social media can be used to study the evolution of public opinion, emotional perception, and prediction of attitudes toward urban issues [39]. Pictures and texts captured on social media are not only methodological tools but also a public practice that can actively participate in the construction of place's identity and image [40].

Image is inseparable from the spatial form formed by BE, including streets, blocks, plots, and buildings [41]. Song et al. further generalized the spatial form factors into permeability, accessibility, and diversity [42]. Some scholars also use volume ratio, density, connectivity, accessibility, and land use mix degree for analysis [43]. Research in Bergen found that plot layout affects the site's image, such as cultural activities, building density, and mixed-use [44]. In addition, for the BE factors of the town hierarchy, good road networks [45], sidewalk systems [46,47], and open spaces [48] are conducive to the formation of happiness, well-being, and unique towns. Iconic buildings play an important role in shaping sustainable cities [49,50]. Considering that towns assume the diversionary and recreational roles of cities, tourist attractions in towns can be seen as iconic nodes. In general, previous studies have focused on the apparent relationship between the two, lacking quantitative analysis of the image dimension and the mechanism of BE's role in image formation. At the same time, no scholars have considered the emotional response of human beings stimulated by BE in the logical chain of image formation.

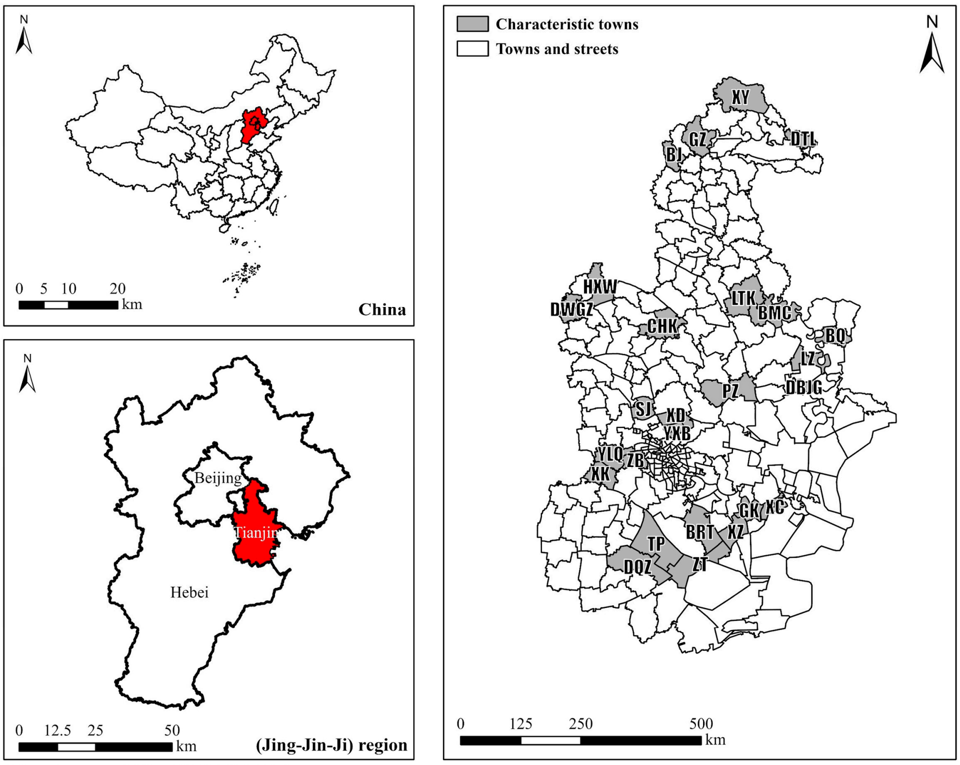
Nevertheless, based on the limitations of the conceptual framework and previous research results, it is necessary to further study the comprehensive influence of multi-dimensional BE factors on the image results in the information age. For example, due to limited data sources, previous studies mainly focused on analyzing the correspondence between images and Lynch's five factors of surfaces, which are not sufficiently instructive for field planning and design. However, the detailed BE factors that can be perceived in daily life have not been fully considered, especially the spatial image at the town scale, which is more closely connected with people. Thus, this study takes the traditional five factors as the basic blueprint and adopts more refined multi-source BE factors to represent Lynch's thoughts, forming a new five-dimensional approach in the digital age.

3. Data and Methods

3.1. Research Area

Located in northern China, Tianjin is a megacity and one of four municipalities. As of 2022, the city's total area is 11,966.45 square kilometers, with a permanent population of 13.63 million. The urbanization rate was 85.11%, an increase of 0.23 percentage points over the end of the previous year. There are 16 districts under Tianjin Municipality, including 263 towns and streets.

This research focuses on exploring the relationship mechanism between town image and BE. Taking towns as the research unit, this is the smallest administrative unit for the urban population census and public service supply in China. This study uses data collected from social media to characterize the image of towns in people's minds. However, due to the unclear development goals and poor cultivation of some towns, pictures and texts of such towns did not appear on social media. Therefore, 26 towns of Tianjin's municipal-level characteristic towns were selected as the research samples (Figure 1).



Plan Approval No. GS(2023)2767

Figure 1. Location of case study sites in Tianjin.

3.2. Methods

3.2.1. Research Process

The study was divided into four steps, the first being data collection and screening; the second step was data processing, such as picture content analysis of deep learning models, NLP, and the computing process of the BE; the third step is the result analysis, including the analysis of the influence mechanism of the addition of the BE and emotions on the UI; discussion and conclusion is the final step (Figure 2). Compared with the traditional research methods based on questionnaire surveys and cognitive maps, the collection of social media data and the development model based on deep learning are new methods for image cognition.

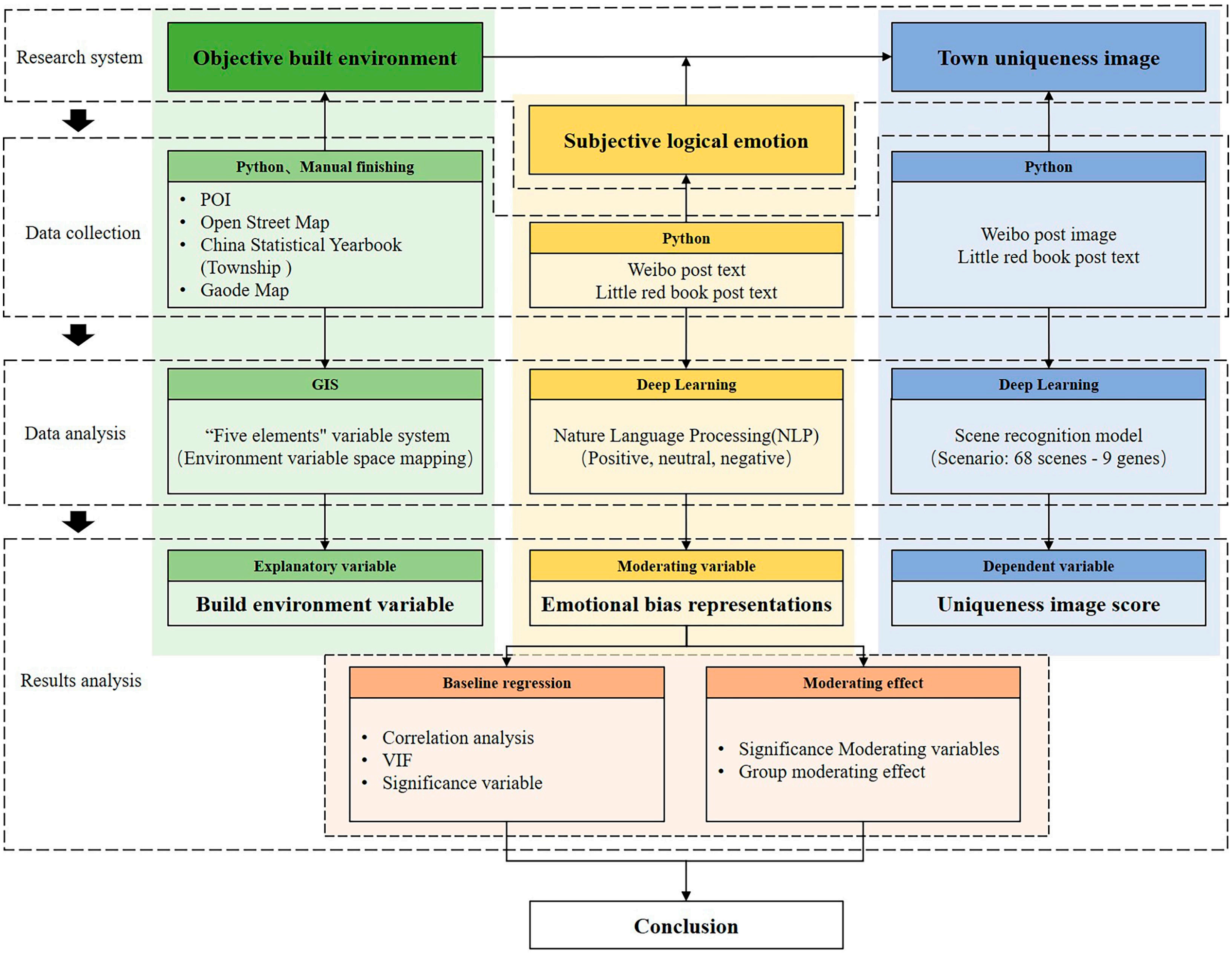


Figure 2. Research process.

3.2.2. Research Model

We first adopted a multiple OLS regression model previously applied to investigate people's movement patterns [51,52] to explore the mechanism relationship between the BE of the town, the subjective logical emotions of people, and the town UI. To ensure the reliability of the subsequent empirical results, we adopt stepwise regression to introduce dependent variables, explanatory variables, moderating variables, and control variables into the model in turn. In this paper, the following baseline model is constructed:

$$UI = \beta_0 + \sum_i \beta_i BE_i + \varepsilon \quad (1)$$

where UI represents the dependent variable, that is, the UI of the town, and the BE_i represents the explanatory variable, that is, the BE. β_0 is the intercept, β_i is the estimated coefficient of the explanatory variable, and ε is the error term.

The positive emotions variable in the emotions dimension as a moderating variable and its interaction term with each BE variable were introduced into Equation (1) to further explain the moderating effect of emotions in the relationship between the BE and the UI of the town, enhance the baseline model, and construct the following model:

$$UI = \beta_0 + \beta_1 BE + \beta_2 EMO + \beta_3 BE \times EMO + \varepsilon \quad (2)$$

Here, β_1 is the coefficient of the explanatory variable BE, EMO represents the moderating variable, that is, emotional cognition, β_2 is the coefficient of the moderating variable, and $BE \times EMO$ represents the influence of emotional cognition regulating the *BE* on the *UI* of the town, and the coefficient is β_3.

3.3. Data

We used five types of data in this study: town image data, text emotions data, POI data, environmental attribute data, and town socio-economic data (Table 1). Known as "Chinese Twitter", Sina Weibo is one of the largest social media platforms in China [53,54]. Little Red Book has also become a very popular social platform in recent years. The town image data came from the pictures posted by people on the two platforms. Text emotions data are the text content published and shared by users. POI data were obtained based on the application programming interface (API) of the Gaode map. Environmental attribute data including administrative boundaries at all levels in Tianjin, related road networks, and building information were obtained from OSM and Gaode Map. The socio-demographic and economic data of the towns came from the 2022 China Statistical Yearbook (Township) released by China's National Bureau of Statistics.

Table 1. Data sources.

Data	Data Source	Data Type
Town image	Sina Weibo (https://m.weibo.cn, accessed on 22 December 2023) Little Red Book (https://www.xiaohongshu.com/explore, accessed on 20 December 2023)	Social media
Text emotions	Sina Weibo (https://m.weibo.cn, accessed on 22 December 2023) Little Red Book (https://www.xiaohongshu.com/explore, accessed on 20 December 2023)	Social media
POI	Gaode Map (https://ditu.amap.com, accessed on 18 December 2023)	Social sensing
Environmental attributes	OpenStreetMap (https://www.openstreetmap.org, accessed on 15 December 2023) Gaode Map (https://ditu.amap.com, accessed on 18 December 2023)	Crowd source
Town social economy	China Statistical Yearbook (Township) (http://www.stats.gov.cn/zs/tjwh/tjkw/tjzl/202302/t20230215_1908003.html, accessed on 15 December 2023)	Government

3.4. Measurement

The measurement is based on the synthesis of the relationship between image and BE in the above paper as a foundation, and in conjunction with the analysis of the factors of BE that play an important role in the formation of happy towns, as explained in the paper. Meanwhile, with Lynch's five factors as a criterion for dimensioning, and taking into account the objective BE of people's permeability, we selected the indicators as comprehensively as possible. The following are measures for some of the variables in image, BE, and emotions. The definitions in Table A1 list the measures for the remaining variables.

3.4.1. Image

The social media pictures were obtained using Python 3.10 to request the official open APIs of Weibo and Little Red Book. Considering the impact of the new crown epidemic on people's daily life behavior and perception, the search time is from January to April 2023, when China implemented an open policy regarding the epidemic. Using the town's name as the keyword and selecting the column of "location check-in" to the search will ensure that the user has an image recognition of the target town. At the same time, pictures that have nothing to do with town impressions, such as personal events posted by users, will be removed. In the end, we collected a total of 11,196 pictures in the study area.

Then, we adopted the VGG19 convolutional neural network model widely used in picture classification for training [30,55]. We collected a total of 68 types of scenes. Merged by the proximity of scene categories and people's perceived similarity, they were reclassified into 9 categories of image genes (Table 2).

Table 2. Image gene classification.

Gene Type	Scenes
Building	Windows, building components, building interiors, building exteriors, building roofs, building nightscapes, stairs, doors, walls, theatres
Public space	Ground, square, hutong, street, corridor, waterfront, water pavilion, courtyard
Landmark	Carving, statues, attraction signs, road signs, door signs, tickets, pagodas, bridges
Cultural custom	Ornaments, performances, lanterns, non-heritage items, windmills, lanterns, paper-cutting, festive events, food, models, New Year paintings, balloons, rickshaws, lion dances, fireworks, writing, characters, folk crafts
Mountain	Mountains, artificial rockery
Water	Water, boating
Animal	Dogs, cats, monkeys, bees, butterflies, deer, dragonflies, tigers, lions, elephants, ornamental fish, peacocks
Plant	Flowers, trees, grass, leaves
Sky	Blue sky, white clouds, night sky, sunset

For the network model we trained on the server, the ratio of the training set to the test set was 7:3 (Figure 3). We trained for 100 epochs to obtain the most stable model, which achieved 93.2% accuracy.

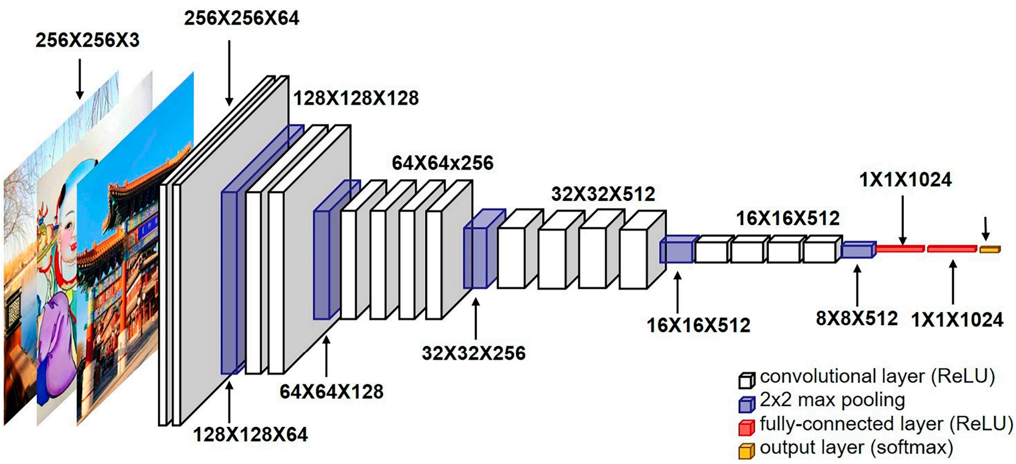


Figure 3. Network model structure for social media image recognition.

The loss of uniqueness affects the creation of livability and modernity of the destination [56]. To further quantify the expressiveness of the town image, we used the *UI* mentioned by Lynch as a measure of the town's characteristic degree. Because towns trend differently on social media, there are differences in the number of pictures that reflect each town's image. Therefore, compared with using standard deviation to measure the degree of dispersion of *UI*, the coefficient of variation can better eliminate the influence of the mean value. This is conducive to obtaining a *UI* score of the town that is close to reality. The formula is as follows:

$$\mathrm{UI} = \frac{\sqrt{\frac{1}{\mathrm{N}}\sum_{i=1}^{\mathrm{N}}(x_i - \mu_i)^2}}{\mu_j} \quad (3)$$

where *UI* is the uniqueness image score, N is the number of image gene categories, the value is 9, x_i is the number of a certain image gene in a single town sample, μ_i is all town samples μ_j is the average number of occurrences of various image genes in a single town sample, and j ranges from 1 to 26.

3.4.2. BE

The road connectivity coefficient reflects the networkability and reliability of the road network and is often used as a measure of the maturity of the network. The higher the coefficient, the fewer broken paths, and the higher the network formation rate, and the formula is as follows:

$$RC = \left[\sum_{i=1}^{n} m_i\right]/\mathrm{N} = \frac{(n_b \times 1 + n_t \times 3 + n_c \times 4 + n_f \times 5)}{(n_b + n_t + n_c + n_f)} \quad (4)$$

where RC is the road connectivity coefficient, N is the number of road network nodes, m_i is the number of edges adjacent to the ith node, n_b is the number of broken roads, n_t is the number of T-shaped intersections, n_c is the number of cross intersections, and n_f is the number of five-way intersections.

The street edge is the external presentation and material basis of the spatial form of the block. Here, the sky view factor is an important spatial morphological parameter. The formula is as follows:

$$SVF = 1 - \sum_{i=1}^{n} \sin \gamma_i / n \quad (5)$$

where SVF is the sky view factor, γ_i is the influence of the terrain height angle on the azimuth angle i, and n is the number of calculated azimuths (n = 36 in this study). The SVF was estimated with a 5 m spatial resolution, and the radius R(m) of influence was 20 grids (20 × 5 = 100 m).

The POI data were crawled for 2022 and totaled 23,456 entries. According to the spatial development of the town scale and the living habits of residents, combined with the classification code of the Gaode platform, POI was regrouped into eight commonly used categories, namely catering, shopping, life services, leisure, business, accommodation, scenic spots, and transportation facilities. We calculated the POI mix using the Shannon Index to measure the strength of regional function, as follows:

$$Y = -\sum_{i=1}^{\mathrm{n}} P_i \log P_i \quad (6)$$

where Y represents the degree of functional mixing, P_i is the proportion of the number of various functional service facilities to the total number of functional service facilities, and the larger the Y value, the higher the degree of mixing.

3.4.3. Text Emotions

Texts on social media are comments posted based on people's perceptions of the town space or afterthoughts of the online pathway. These texts are colored by emotions towards the town. By using Python to crawl tweets posted by users about towns, we collected 57,719 pieces of text data.

The emotions analysis module on Baidu Cloud's Nature Language Processing (NLP) platform is based on a Chinese massive Internet corpus, combined with deep learning network model algorithms which can effectively identify emotional tendencies and provide probability values. We used the platform's sentiment analysis interface (https://cloud.baidu.com/product/nlp_apply/sentiment_classify, accessed on 22 December 2023) to analyze and process the text. The essence of emotions analysis is to investigate the rationale for emotional expression in text and to estimate the emotional orientation (i.e., positive, neutral, or negative) towards the subject of the text [57]. Our NLP model achieves an accuracy of 95.3% and selects the value of the positive emotions reflected in the text as a variable.

3.5. Variable Summary

Table A1 shows and summarizes the statistics for all variables in this study. The dependent variable is the UI score of the town. The explanatory variables characterize the

BE. Moderators are the positive emotions that people interact with in their minds after being exposed to the BE.

4. Results

4.1. Baseline Results

First, we performed a correlation analysis of all variables. As shown in Figure 4, there are strong correlations between road network and sidewalk, time to downtown and reachability, transportation and commercial, and population density, commercial and sidewalk combinations among multiple explanatory variables. We only kept the sidewalk for the next step of modeling to reduce the interaction between the explanatory variables. Next, the variables of variance inflation factor (VIF) values > 10 in the baseline model were removed by multicollinearity testing, namely building height and street width to height ratio. The remaining variables in the model had VIF values of <10, which means that there were no serious multicollinearity problems. We then conducted baseline model analysis to investigate the direct impact of BE variables on the UI.

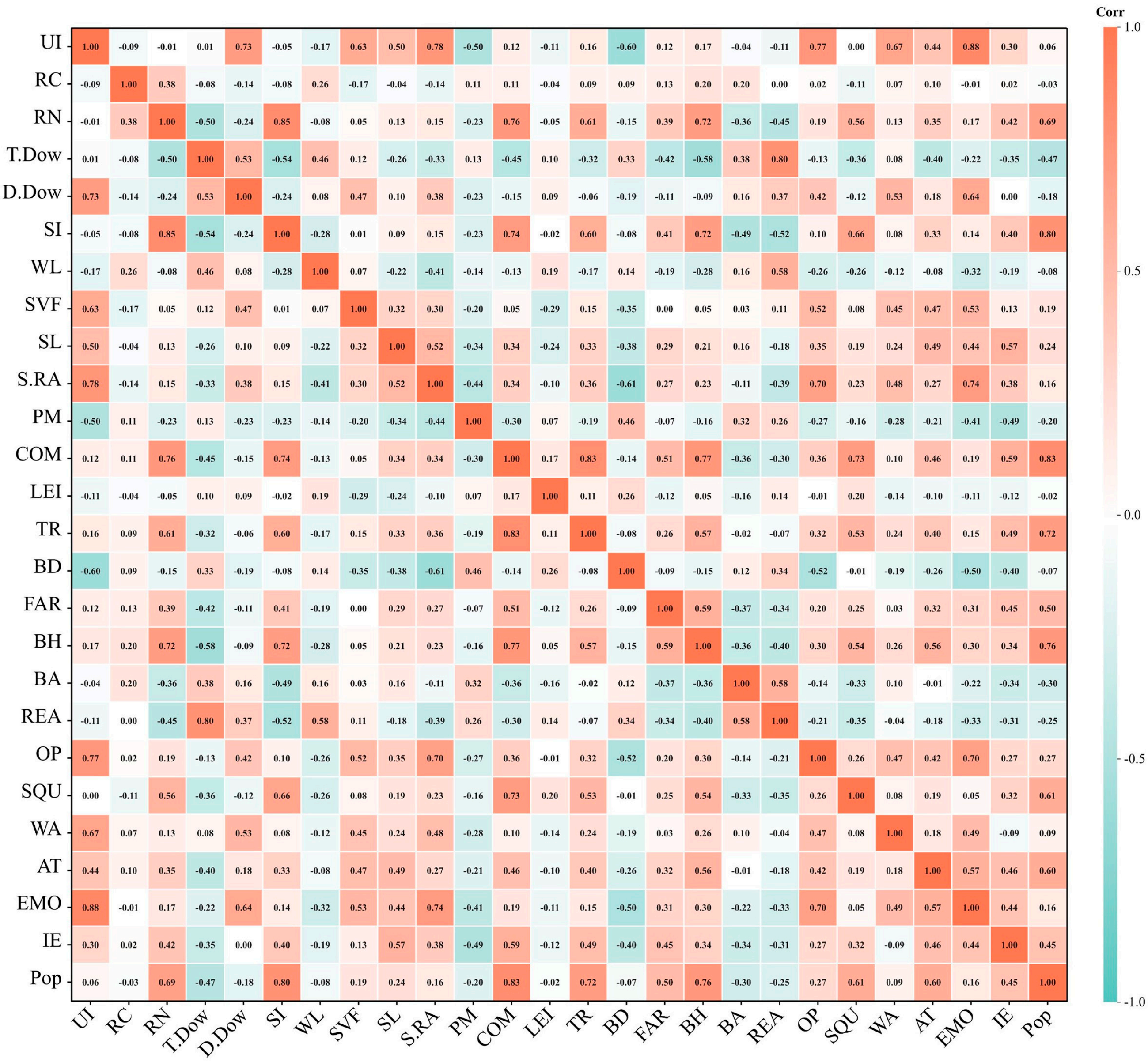


Figure 4. Correlation matrix of the tested variable.

From the regression results in model 1 to model 5 (Table A2), it can be seen that positive emotions have a positive effect on the UI. For the hierarchical regression results of the five types of BE, only the edge class alone had no significant association with the UI. However, the addition of positive emotions can transform some variables that are not otherwise significant into significant variables, such as the sky view factor and POI mix block area. Among them, the sky view factor in the edge and POI mix in the region were transformed into significant negative effects. Model 6 shows the simultaneous existence of five types of BE and the result of adding positive emotions. In Model 6-1, the distance to downtown, sidewalk, street length, open space, water area, and tourist attraction were significantly positively correlated with UI. The effects of building density, block area, and square were significantly negative. It is worth noting that the block area becomes insignificant when positive emotions are added. This suggests that people have a positive attitude that may offset the negative effects of accessibility. When the above variables were continuously layered into the model, the adjusted R^2 from model 1 to model 6 continued to increase from the minimum value of 0.199 to 0.977, and the value of F was also significant. This shows that the performance of these models has been significantly improved, and stable optimization has been carried out. At the same time, it is reasonable to state the combination of selected variables. The above analysis shows that the addition of positive emotions will lead to changes in the direction and significance effects of BE, indicating that there is a hidden mechanism of action.

4.2. Moderating Effects

We added the interaction terms of each BE variable and positive emotions to the moderation model to examine the effect of positive emotions in regulating the relationship between the BE and UI (Table A3). The regression results of interaction terms in models 1 to 13 show that positive emotions can increase or mitigate the influence of different BE variables on the UI. It is worth mentioning that road connectivity, sidewalk, POI mix, building density, open space, square, water area, and tourist attraction alone do not show a significant relationship with the UI. However, with the addition of the regulatory variable of positive emotions, they all present a significant influence relationship. Distance to downtown, water length, and sky view factors have a significant impact on UI and interact with each other. This shows that positive emotions have a moderating effect on the relationship between the BE and UI. In addition, positive emotions had the greatest moderating effect on the effect of the sky view factor ($B = 0.281$) on UI.

We plotted the interaction map of positive emotion's moderating effects on the relationship between the BE variables and the UI to show the specific direction and intensity of action (Figure 5). From Figure 5b,g–j, it can be seen that the slopes of High EMO and Low EMO are similar. This shows that positive emotions have a weak moderating effect on the relationship between distance to downtown, building density, open space, water area, and UI. For Figure 5c,d,k, the main effect between the BE variable and the UI at this time is a positive influence relationship. Here, in terms of sidewalk and tourist attraction, High EMO has a smaller slope than Low EMO, indicating that people holding higher positive emotions will weaken the positive effect between the sidewalk, tourist attraction, and the UI. Regarding water length, the regulatory effect produced by positive emotions has a significant strengthening effect. In Figure 5a,e,f, the three BE variables have a negative effect relationship with the main effect of the UI. In terms of road connectivity, the slope of High EMO is larger than that of Low EMO, indicating that the moderating effects of positive emotions significantly inhibit the negative effect of road connectivity on the UI. At once, there is an intersection between High and Low EMO, indicating that road connectivity and positive emotions have a substitution relationship in influencing the UI. On the other hand, positive emotions significantly promote the negative effects of the sky view factor and POI mix on the UI.

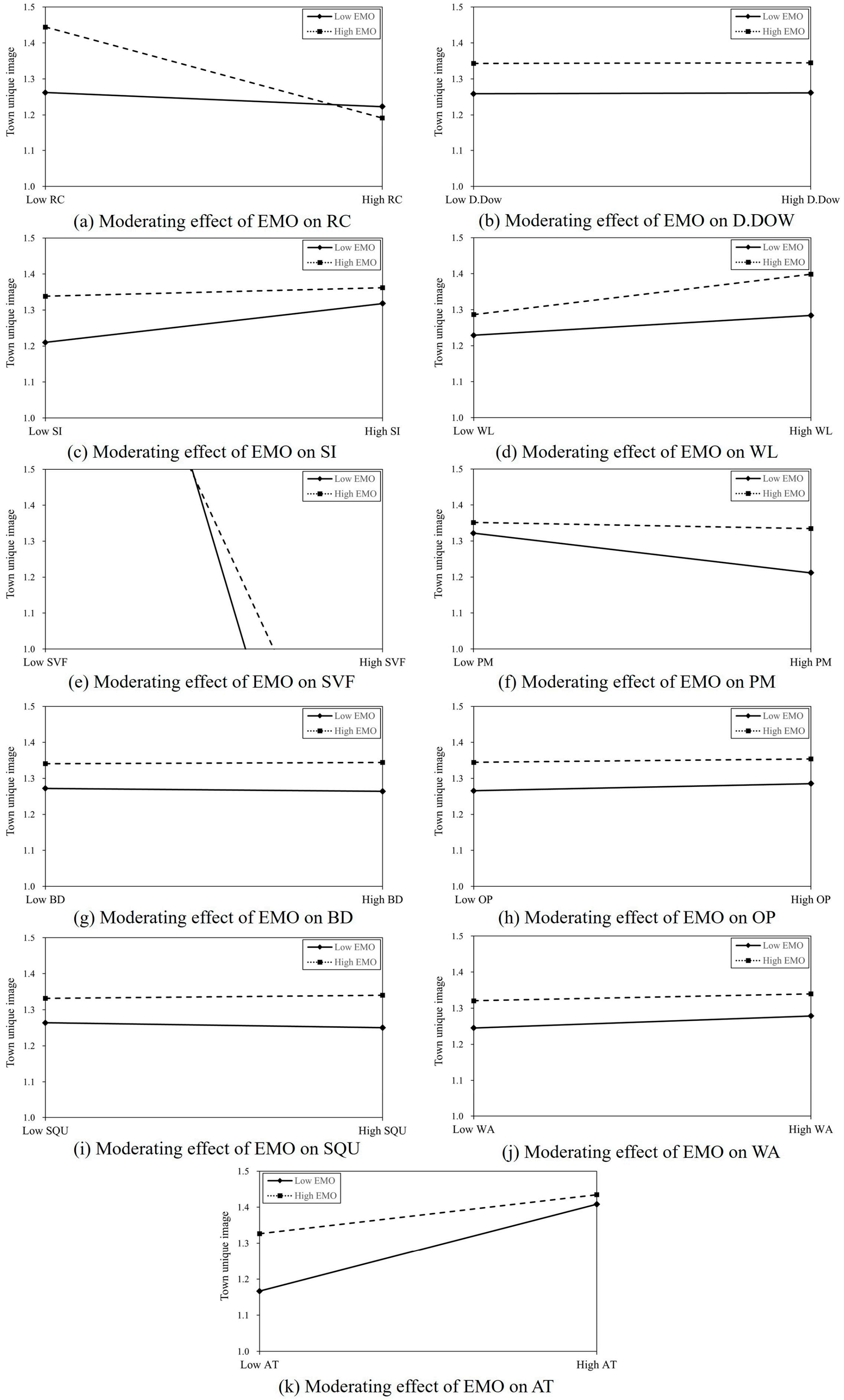


Figure 5. The moderating effect of positive emotion.

5. Discussion

In this study, we used five novel dimensions based on multi-source data to assess the impact of BE on UI. The results of the baseline model show that the edge dimension alone does not show a significant relationship with the UI. This finding dovetails with previous city scale studies, where the edge may not be an important dimension for the image [58]. This also complements the findings of the weaker boundary nature of images under different settlement hierarchies. It can provide possibilities and a theoretical basis for the subsequent construction of image networks by urban planners. However, when the multidimensional BE variables were present simultaneously, the average length of streets became significantly positively correlated. Streets in towns are usually smaller than in cities. We can make the UI more prominent by planning longer streets in a way that is appropriate to the local environment. As the driving distance from the town to the urban center increases, the chance of exposure to the natural environment becomes more likely. As a result, UI improvements are achievable by increasing the amount of greenery and view openings located along the pathway process between multiple towns. Open spaces can highlight the vitality of spaces through a humanistic atmosphere and enhance their character [59]. The redevelopment of blue spaces can improve vitality, identity, and attractiveness [60,61]. The positive role of tourist attractions is inseparable from tourism as a pillar of town development [62].

The effects produced by the moderation model showed that positive emotions could significantly enhance or weaken the influence of some BE variables on the UI (Table A2 and Figure 5). For the BE variables with obvious modulating effect intensity, positive emotions had positive moderating effects on water length, tourist attraction density, and sidewalk density on UI. The water system has certain benefits in inducing positive emotions and reducing negative emotions and stress [63], which can cause happiness in people [64]. By upgrading the level and popularity of existing tourist attractions, and developing tourism resources that take into account the local environment and customs, thereby enhancing uniqueness, the perception generated by sidewalk stimulation will influence subsequent behavior [65], demonstrated in this study by people's image expression on social media. The construction of footpaths is based on a planning scale appropriate to the needs of a people-centered approach. Conversely, positive emotions negatively moderate the road connectivity coefficient, sky view factor, and POI mix. This shows that the higher the road network formation rate of the road network, more the improved positive emotions make the UI appear ordinary. The sky view factor in towns is generally larger, and the UI is reduced for people. The higher the degree of POI mix, the greater the contemporary relevance of the town [66,67], raising people's positive emotions. However, as the diversity of facilities increases, people's sense of uniqueness will be diminished.

6. Conclusions and Limitations

This study took the characteristic towns of Tianjin, a typical megacity in China, as the research object to explore the mechanism between town image and the BE. We developed two variables, UI and positive emotions, to study town image and emotions. Combined with rich multi-source big data, the BE factors of towns were fully integrated. The findings showed that BE has a direct effect on town UI. Simultaneously, positive emotions have a complex moderating effect on the relationship between the two. The generation of images is inseparable from the process of stimulating the human body in the BE of the town, and then interacting with logical cognition. Thus, a more detailed analysis of the moderating effects is conducive to a deeper understanding of the relationship between BE and image, which helps to adjust the coordination between planning policy and design strategy at the government level. This can optimize the allocation of resources from the perspective of space users to achieve sustainable development goals.

Considering that previous research on images paid more attention to the surface and structural images of cities or urban internal spaces, but ignored the quantification of images and the interaction mechanisms of subjective and objective interaction, as well as the study of images at the town scale, this study mainly fills three important research gaps:

(1) The acquisition of multi-source big data and the method of deep learning, so that the image can be accurately quantified. As Lynch puts it, "If enough probe arrays are used, a comprehensive picture is not far from the truth" [68].
(2) The exploration of the influence of the BE on the UI at the town scale.
(3) The reveal of how positive emotion regulates the relationship between different BE variables and the UI.

However, this study had some limitations: First, due to the unstructured and voluntary nature of social media data, UI data may be underrepresented for the elderly population and low-income people [69]. In future studies, more data sources can be added, such as questionnaires, live interviews, etc. This can form a research system of image differences for different age groups. Moreover, due to manpower and time constraints, this study is based on an empirical investigation of a characteristic town in Tianjin, China, resulting in a limited number of research cases. After that, it can be extended to the study of town image at the level of the Tianjin metropolitan area or even urban agglomeration, and enhance the contrast between horizontal and vertical dimensions. This will make the data more convincing. These deficiencies can be explored in more detail in future studies.

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Appendix A

Table A1. Definition and summary of variables.

Domains	Variable	Mean	Std.	Min	Max	Definition
Dependent variable	Uniqueness image (UI)	1.263	0.126	1.016	1.628	The degree of dispersion of the town uniqueness image
Explanatory variables						
Path (P)	Road connectivity (RC)	2.162	0.270	1.625	2.800	Strength of interconnection between nodes by roads
	Road network (RN)	3.150	0.583	2.400	4.580	The ratio of the length of the road to the area of the town
	Time to downtown (T.Dow)	103.500	35.881	55.000	196.000	Actual time to downtown center (minute)
	Distance to downtown (D.Dow)	65.607	42.721	20.422	186.730	Driving distance to the downtown center (km)
	Sidewalk (SI)	1.314	0.498	0.509	2.570	The ratio of the length of the sidewalk to the area of the town (/km)
Edge (E)	Water length (WL)	1.152	0.880	0.047	3.963	The ratio of the length of the river system to the area of the town (%)
	Sky view factor (SVF)	0.955	0.034	0.854	0.989	Proportion of the sky visible from the street valley
	Street length (SL)	338.033	115.435	169.768	673.772	Average length of street (m)
	Street width to height ratio (S.RA)	1.540	0.454	0.711	2.607	The ratio of street width to building height along the street
District (D)	POI Mix (PM)	1.266	0.436	0.340	1.883	Mean entropy of town POI categories
	Commercial (COM)	13.279	14.973	1.255	63.934	The density of commercial facilities (/km^2)
	Leisure (LEI)	0.625	1.211	0.000	4.919	The ratio of the number of transportation facilities to the area of the town (/km^2)
	Transportation (TR)	0.785	0.584	0.129	2.480	The ratio of the number of commercial facilities to the area of the town (/km^2)
	Building density (BD)	3.726	2.894	0.315	10.952	The ratio of the base area of the building to the area of the town (%)
	Floor-area ratio (FAR)	0.203	0.169	0.013	0.753	Total areas of building space of all kinds divided by the total areas within a plot (%)
	Building height (BH)	14.495	3.771	11.677	27.613	Average height of the building (m)
	Block area (BA)	7.577	10.114	0.849	35.665	The average size of the block (ha)
	Reachability (REA)	48.822	20.158	13.093	117.900	Average travel time from town to other towns (min)
Node (N)	Open space (OP)	6.028	2.872	1.051	10.798	The ratio of the total area of parks and green spaces to the area of the town (%)
	Square (SQU)	1.277	2.037	0.000	7.832	The ratio of the area of the square to the area of the town (%)
	Water area (WA)	4.658	1.946	0.373	6.965	The ratio of the area of the water system to the area of the town (%)
Landmark (L)	Tourist Attraction (AT)	0.253	0.271	0.000	0.995	The ratio of the number of tourist attractions to the area of the town. (/km^2)
Moderating variables	Positive emotions (EMO)	69.256	3.336	64.179	82.707	Confidence probability of positive sentiment of the text (%)
Control variables	Industrial enterprises (IE)	292.846	326.982	7.000	1137.000	Number of industrial establishments
	Population density (Pop)	706.345	433.635	144.322	1836.771	Number of permanent residents per net area (/km^2)

Note: Std. = standard deviation.

Table A2. The results of the baseline model for UI.

Variables		Model 1-1 B (S.E.)	Model 1-2 B (S.E.)	Model 2-1 B (S.E.)	Model 2-2 B (S.E.)	Model 3-1 B (S.E.)	Model 3-2 B (S.E.)	Model 4-1 B (S.E.)	Model 4-2 B (S.E.)	Model 5-1 B (S.E.)	Model 5-2 B (S.E.)	Model 6-1 B (S.E.)	Model 6-2 B (S.E.)
Explanatory variable													
Path	RC	0.009 (0.055)	−0.014 (0.039)									−0.004 (0.018)	−0.010 (0.021)
	D.Dow	0.002 *** (0.000)	0.001 ** (0.000)									0.001 *** (0.000)	0.001 *** (0.000)
	SI	0.098 ** (0.036)	0.067 ** (0.026)									0.080 *** (0.014)	0.076 *** (0.016)
Boundary	WL			−0.009 (0.030)	0.020 (0.014)							−0.006 (0.006)	−0.003 (0.008)
	SVF			−1.496 (1.098)	−0.953 * (0.520)							−0.368 (0.251)	−0.327 (0.268)
	SL			0.000 (0.000)	0.000 (0.000)							0.000 *** (0.000)	0.000 *** (0.000)
District	PM					−0.096 (0.060)	−0.067 ** (0.028)					−0.025 (0.014)	−0.024 (0.015)
	BD					−0.020 ** (0.008)	−0.008 * (0.004)					−0.008 *** (0.002)	−0.008 *** (0.002)
	BA					0.002 (0.002)	0.002 ** (0.001)					−0.001 ** (0.001)	−0.001 (0.001)
Code	OP							0.024 *** (0.005)	0.013 ** (0.005)			0.010 *** (0.002)	0.010 *** (0.002)
	SQU							−0.011 (0.007)	−0.006 (0.006)			−0.007 ** (0.003)	−0.006 * (0.003)
	WA							0.031 *** (0.007)	0.021 *** (0.006)			0.012 ** (0.004)	0.012 ** (0.004)
Sign	AT									0.268 ** (0.108)	−0.021 (0.073)	0.106 *** (0.027)	0.092 ** (0.037)
Moderating variables													
	EMO		0.024 *** (0.005)		0.035 *** (0.004)		0.002 *** (0.001)		0.018 *** (0.005)		0.036 *** (0.005)		0.003 (0.004)

Table A2. *Cont.*

Variables	Model 1-1 B (S.E.)	Model 1-2 B (S.E.)	Model 2-1 B (S.E.)	Model 2-2 B (S.E.)	Model 3-1 B (S.E.)	Model 3-2 B (S.E.)	Model 4-1 B (S.E.)	Model 4-2 B (S.E.)	Model 5-1 B (S.E.)	Model 5-2 B (S.E.)	Model 6-1 B (S.E.)	Model 6-2 B (S.E.)
Control variables												
IE	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 * (0.000)	0.000 *** (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 ** (0.000)	0.000 ** (0.000)
Pop	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 ** (0.000)	0.000 ** (0.000)
Adj.R^2	0.663	0.834	−0.010	0.777	0.300	0.845	0.783	0.874	0.199	0.750	0.978	0.977
F	10.836 ***	21.873 ***	0.950	15.498 ***	3.141 **	23.794 ***	19.042 ***	29.783 ***	3.065 **	19.765 ***	75.544 ***	66.242 ***

Note: *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

Table A3. The results of positive emotions moderating effects on UI.

Variables	Model-1 B (S.E.)	Model-2 B (S.E.)	Model-3 B (S.E.)	Model-4 B (S.E.)	Model-5 B (S.E.)	Model-6 B (S.E.)	Model-7 B (S.E.)	Model-8 B (S.E.)	Model-9 B (S.E.)	Model-10 B (S.E.)	Model-11 B (S.E.)	Model-12 B (S.E.)	Model-13 B (S.E.)
RC	−0.073 (0.047)												
RC × EMO	−0.053 * (0.029)												
D.Dow		0.001 *** (0.000)											
D.Dow × EMO		0.000 *** (0.000)											
SI			0.032 (0.025)										
SI × EMO			−0.021 *** (0.006)										
WL				0.042 ** (0.018)									

Table A3. *Cont.*

Variables	Model-1	Model-2	Model-3	Model-4	Model-5	Model-6	Model-7	Model-8	Model-9	Model-10	Model-11	Model-12	Model-13
	B (S.E.)	B (S.E.)	B (S.E.)	B (S.E.)	B (S.E.)	B (S.E.)	B (S.E.)	B (S.E.)	B (S.E.)	B (S.E.)	B (S.E.)	B (S.E.)	B (S.E.)
WL × EMO				0.014 ** (0.006)									
SVF					−1.295 ** (0.525)								
SVF × EMO					0.281 * (0.135)								
SL						0.000 (0.000)							
SL × EMO						0.000 (0.000)							
PM							−0.032 (0.034)						
PM × EMO							0.023 ** (0.011)						
BD								−0.001 (0.006)					
BD × EMO								0.003 ** (0.001)					
BA									0.004 ** (0.002)				
BA × EMO									0.001 (0.001)				
OP										0.007 (0.006)			
OP × EMO										−0.003 ** (0.001)			
SQU											−0.001 (0.008)		

Table A3. *Cont.*

Variables	Model-1	Model-2	Model-3	Model-4	Model-5	Model-6	Model-7	Model-8	Model-9	Model-10	Model-11	Model-12	Model-13
	B (S.E.)	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**	**B (S.E.)**
SQU × EMO											0.006 * (0.003)		
WA												0.013 (0.008)	
WA × EMO												−0.004 ** (0.002)	
AT													0.087 (0.063)
AT × EMO													−0.033 *** (0.009)
EMO	0.038 *** (0.004)	0.042 ** (0.005)	0.043 *** (0.004)	0.043 *** (0.005)	0.033 *** (0.004)	0.036 *** (0.005)	0.038 *** (0.004)	0.037 *** (0.005)	0.040 *** (0.005)	0.037 *** (0.006)	0.040 *** (0.005)	0.034 *** (0.006)	0.047 *** (0.005)
IE	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Pop	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 * (0.000)
R^2	0.826	0.915	0.891	0.840	0.846	0.790	0.863	0.863	0.833	0.883	0.82	0.889	0.880
F	19.019 ***	43.220 ***	32.722 ***	21.028 ***	21.984 ***	15.071 **	25.121 ***	25.087 ***	19.954 ***	30.099 ***	18.209 ***	31.887 ***	29.239 ***

Note: *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$.

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