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Retraction

Retracted: Using Social Media Data to Explore Urban Land Value and Sentiment Inequality: A Case Study of Xiamen, China

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Z. Gai, C. Fan, S. Shen et al., "Using Social Media Data to Explore Urban Land Value and Sentiment Inequality: A Case Study of Xiamen, China," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 1456382, 14 pages, 2022.

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Research Article

Using Social Media Data to Explore Urban Land Value and Sentiment Inequality: A Case Study of Xiamen, China

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Differences in urban land values affect residents' living experiences and may contribute to sentiment inequality. Due to the popularity of smart mobile devices and social media platforms, online tweets with location information can be used as objective information to reflect sentiment differences of urban residents in different locations, overcoming the limitations of previous studies with small sample sizes or a lack of spatial information. Sentiment quantification based on deep learning enables the identification of spatial patterns of urban residents' sentiments. It also provides a new approach for analyzing data from big data platforms using an intelligent computing platform. This paper quantitatively analyzes the sentiment contained in social media tweets using a deep learning sentiment analysis algorithm to reveal inequalities between urban residents' sentiments and land values. The Baidu Intelligent Cloud sentiment analysis platform is used to identify 460,000 Weibo tweets in Xiamen, China, in 2020. We quantitatively analyze the positive and negative sentiments of residents and create a spatial distribution map. The concentration curve indicates sentiment inequality and the impact of high land values on residents' sentiments. The positive sentiment concentration index (CI) and correlation analysis show that the CI value is 0.07, and significant sentiment inequality exists due to the high land value. The use of social media tweet data to analyze sentiment inequality provides a reference for future interdisciplinary research in psychology, urban planning, geography, and sociology. The proposed approach of analyzing social media data using an intelligent computing platform provides new insights into multiplatform data interaction in the context of the Internet of Everything.

1. Introduction

Sentiments are an important aspect of mental health and are affected by personal experience, objective knowledge, and factors related to people's environment. Sentiments are an intuitive expression of a person's well-being and a self-assessment of life satisfaction. Research has shown a strong causal relationship between sentiments and health [1]. The World Health Organization's definition of health includes physical, mental, social, and moral health [2]. When individuals exhibit negative sentiments, their quality of life decreases; thus, intense negative sentiments are detrimental to health [3, 4].

According to the 2019 State of the Global Sentiment Report, more than 35% of people globally are affected by negative environmental factors and often exhibit negative sentiments. In an urban environment, multiple spatial elements lead to substantial differences in residents' living conditions and experiences, which may reflect large sentiment differences, resulting in unbalanced regional development and unequal health of residents [5, 6]. Therefore, observations and analyses of urban residents' sentiments can provide urban planning decision-makers with feedback to inform planning decisions, narrowing regional development differences and promoting environmental health and equity [7–9].

Due to technological advances in smart devices and big data in recent years, sentiment research has shifted from a focus on subjective cognition to objective data analysis. Social media data has a wide range of applications in various fields. Most studies have used twitter data for text analysis and recognition for evaluation and prediction studies in the fields of economy, society, market, policy, and public events [10–12]. Although recent studies utilized quantitative techniques, few evaluated the causes of spatial differences in sentiments from sociology and public health perspectives, and wealth-biased inequality has been ignored [13]. In urban spaces, sentiments are the best indicator of mental health. Many factors affect residents' sentiments, but the dominant factors are the living space and environment, such as the location, transportation convenience, social structure, education, and medical resources. The land value can comprehensively and quantitatively express the wealth level of an area to quantify the influence of the above spatial factors [14–18]. However, it remains unclear whether differences in residents' sentiments are related to spatial wealth imbalances, which generate inequalities. The impact of changes in land value across different land use types on residents' sentiment is also unknown.

Therefore, this study uses social media big data and deep learning-based sentiment analysis to evaluate the relationship between residents' sentiment and urban land value in different land-use types from the perspective of health equity. This approach provides insights into sentiment inequality to improve sentiments in cities using multiple platforms and data types, which is superior to single-platform data to reflect global characteristics and meet the data processing and fusion requirements of complex Internet of Things applications [19].

2. Literature Review

2.1. Review on Sentiment Analysis. Previous research on sentiments has rarely quantified sentiments. Studies conducted before the 21st century generally assumed that sentiments were highly subjective, abstract, dynamic, and difficult to quantify. Therefore, research on sentiments was limited to subjective cognitive aspects, such as place attachment and place complex, and the primary research methods included conceptual analysis and questionnaire surveys [20–22]. Since the beginning of the 21st century, environmental degradation due to urbanization has become more pronounced. Interdisciplinary research in geography and sociology has been conducted to evaluate the spatial aspect of human sentiments, developing the field of sentiment geography [23, 24]. As a product of interdisciplinary development, scholars in different fields have investigated sentiments from various aspects, such as gender, culture, ethics, and mental health. Most of this research focused on people's behaviors and daily life, extending to the study of people's living environments and locations, such as the impact of food establishments and leisure places on sentiments [25, 26]. At this stage, few studies analyzed in-depth the relationship between sentiments and the spatial environment.

The popularization of wireless devices and smart sensors has significantly improved the speed and capacity of data acquisition, simplifying the acquisition and statistical analysis of sentiment data [27–31]. The ability to collect large amounts of samples increases the chance of reflecting residents' sentiments accurately and describing sentiment changes. Examples include sentiments on urban green space, streetscape, transportation mode, visual experience, and architectural environment. As a result, the number of sentiment studies reflecting the environment from multiple perspectives has increased [32–34]. Data sources have also become more extensive. Social media, questionnaires, and app reviews have become crucial sources of research data. The processing and quantification of data have benefitted from developments in deep learning technology. Intelligent recognition methods, such as text recognition in tweet content, face recognition in photos, and emoji recognition, have high efficiency and high precision. Text recognition is a common method. Words, expressions, and pictures are preferentially used to express personal feelings in nonface-to-face communications on social networks [35]. Sentiment information conveyed by text is more complex than using expressions and pictures. More personal sentiments can be expressed by fusing sentiment words and modifiers to reflect an individual's environment and explain the reasons for sentiment changes. Due to the complexity of word combinations and the ease of commenting on social networks, deep learning and intelligent recognition are also highly suitable for processing and statistical analysis of large-volume sentiment data [36–38].

2.2. Review on the Relationship between Land Value and Residents' Sentiments. The land value affects the living experience of residents, and sentiments are the direct expression of the residents' feelings. From an economic point of view, rising land values are conducive to increasing the asset value of owning one or more homes, thereby increasing the positive sentiment of homeowners. However, rising land values increase the living cost of renters and reduce the positive sentiments of renters [39]. From a geographical point of view, a high land value is often associated with better education, medical care, shopping, living facilities, environment, and landscape, and more convenient transportation. Thus, residents have more positive sentiments in areas with higher land values. Areas with low land values tend to lower residents' positive sentiments because of poor living conditions [40]. From a sociological point of view, residents in high land value areas are dominated by social elites and people with high income and higher education. The residents have low mobility and higher positive sentiments. In contrast, areas with a low land value have high population mobility and more class mixing, reducing the positive sentiments of residents. The impact of the land value on the sentiments of different groups of residents is complex and diverse, and sentiment inequality can be exacerbated by multiple factors [41]. Land value can affect changes in the spatial environment in many ways, which directly affect the living experience of residents. Therefore, it is necessary to investigate the relationship between sentiments and land value to clarify sentiment inequality from the perspectives of urban geography, sociology, and public health. Few studies have used social media data to study land values and residents' sentiments. Scholars have found both negative and positive correlations between sentiment and land value [42, 43]. The reason may be that sentiments derived from social media data in these studies were scored using keyword dictionaries, making it difficult to quantify sentiments accurately. This approach cannot distinguish whether a high-quality living environment (i.e., a high land value) has a positive effect on the sentiment, or whether the higher cost of living in an area with a high land value has a negative effect on the sentiment [44–46]. In addition, most studies did not classify the land-use types (such as green space and industrial land), resulting in inconsistent research conclusions.

At present, the quantitative analysis methods of sentiments are widely studied and applied in many fields. However, most studies are based on a single data type, there are few studies on multidata interaction, and the research results are not easy to reproduce and share. Although there have been many studies on the built environment and residents' life experience, there is a lack of analysis on the impact of land value on residents' sentiments. Exploring the sentiment inequality of residents caused by differences in land value can help improve the living environment and promote social equity by regulating land resources.

3. Method

3.1. Using Social Media Data to Study Sentiment Inequality. Health inequality is a systematic difference in the health status of different social groups. Many scholars have researched health inequality from multiple perspectives, such as income, social outcome, gender, and age [47–51]. Sentiments are a crucial aspect of mental health and are affected by various spatial environmental factors, resulting in health inequalities. Therefore, this paper explores the causes of sentiment and land value inequality from a health inequality perspective using three steps: sentiment analysis based on deep learning, land value analysis, and inequality analysis and quantification. The research methods and process of this paper are shown in Figure 1. The results can improve our understanding of and research on health inequalities.

3.2. Quantitative Sentiment Analysis Using Social Media Data and Deep Learning

3.2.1. Social Media Data Processing Methods. Social media check-in data are more suitable for urban structure identification and crowd behavior research than other big data sources such as mobile phone data. Since check-in events are based on people's conscious behavior, people will only check in at a location when they plan to stay for a relatively long time and believe there is something worth recording [52]. Therefore, Python or other programming languages can be used to crawl the tweet content of a social media platform to obtain batch data on public information, such as the geographic location, generation time, tweet content, and user name [53, 54].

The first step is data cleaning and segmentation to ensure high-quality data as input into the text analysis algorithm. This step is critical in natural language processing because it provides machine-readable text, increasing the accuracy of the results. In general, it is necessary to filter and remove meaningless text or symbols, such as duplicates and garbled characters, e.g., URLs, Html, tags, email addresses, and non-ASCII characters [55] so that the deep learning sample library can identify most of the data content.

3.2.2. Sentiment Quantification in Social Media Text Data Based on Deep Learning. Sentiment analysis can be performed using deep learning classifiers that differentiate between emojis and text and determine the degree of sentiment expressed in the text. For example, some scholars used sentiment dictionaries to study the content of social media tweets and used supervised learning to identify and quantify sentiments [56–58]. Unlike offline dictionary analysis methods, the code used in the intelligent analysis platform is portable, and the results are reproducible. More importantly, an intelligent analysis platform enables data interaction between multiple platforms. The Baidu intelligent cloud sentiment analysis platform (https://aip.baidubce.com/) used in this study utilizes the sentiment knowledge enhanced pretraining (SKEP) algorithm. First, the SKEP automatically identifies sentiment knowledge from a large amount of unlabeled data based on statistical methods. Then, the SKEP masks some words in the input sentence. Finally, the SKEP performs three optimization steps: sentiment collocation, sentiment word prediction, and sentiment polarity classification. By conducting pretraining with sentiment-oriented optimization objectives, the automatically identified sentiment knowledge is embedded into the semantic representation of the model [59]. The accuracy of the model for different datasets ranges from 72.9% to 97.6%, and it has been widely used in consumer decision-making, public opinion analysis, personalized recommendation, and other fields. The platform supports more than 80,000 users, making it one of the most comprehensive and widely used service platforms in sentiment analysis. We divide the sentiments into positive and negative sentiments according to the results of intelligent sentiment recognition to facilitate sentiment quantification. The score is in the range of 0 to 1 to enable comparisons between multiple dimensions.

Due to a large amount of social media location data, maps can be cluttered when the data are represented using traditional thematic maps such as symbols or dot distribution maps. Therefore, we use a grid to map the data and use colors or patterns to differentiate the grids according to the subject information [60]. We selected a 300 m by 300 m grid for spatial statistics. This scale is suitable for the identification of land-use samples and for comparing results with other data of the same spatial resolution, such as remote sensing images, land cover, night lights, and analysis of urban land-use changes.

In addition, due to the small number of samples in some grids (such as forest areas), we remove grids with less than

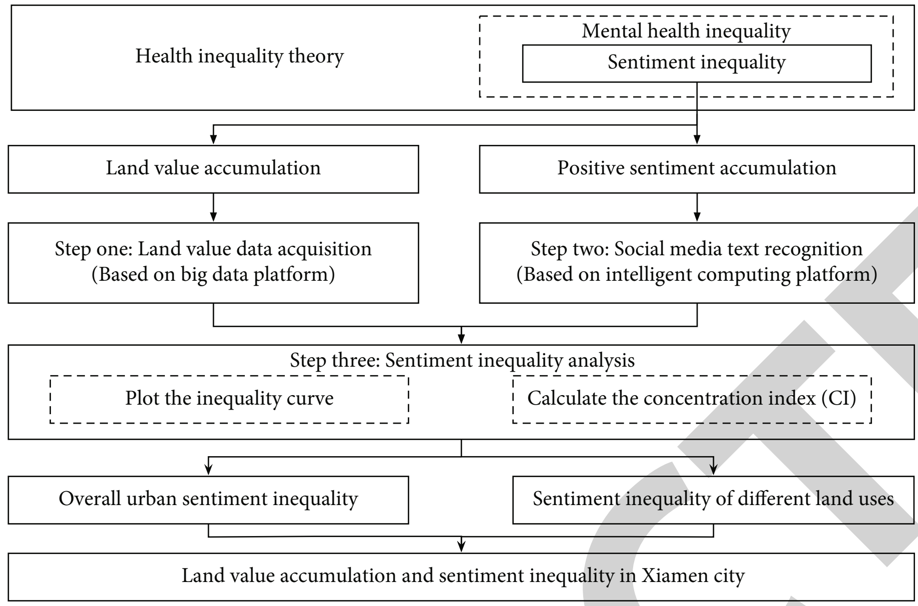


Figure 1: Research method and process.

ten sample points. Equation (1) is used to obtain the mean of the sentiments in each grid is to ensure a normal distribution and eliminate the influence of outliers in the sentiment data [61]:

$$\widehat{Y}_r = \left(\frac{N}{n}\right)\left[\varphi\left(\varphi^{-1}\left(\sum_{i=1}^{r-1}\frac{n_i}{N}\right)\right) - \varphi\left(\varphi^{-1}\left(\sum_{i=1}^{r}\frac{n_i}{N}\right)\right)\right], \quad (1)$$

where φ^{-1} is the inverse standard normal cumulative density function, r is the score range of positive sentiments, n_i is the number of cases in the range r, N is the total number of cases, $\widehat{Y}_r$ is the normal score for range r, and φ is the standard normal density function. Higher Y values represent higher positive sentiments in the grid.

3.3. Acquisition of Land Value Data Using Real Estate Websites. In the era of big data, the combination of real estate data and the Internet plus has enabled a real estate information network. Current real estate price data on the Internet are generally collected by designated staff, uploaded through terminals, and published on the Internet by relevant institutions, providing information on real estate transactions. There are relatively few fine-scale urban geospatial datasets (e.g., transportation infrastructure and housing units) due to differences in land value standards and policy impacts in different cities, gaps in data sharing policies, and confidentiality issues [62]. Therefore, most studies have used web crawlers to obtain public real estate information in batches from real estate transaction websites [63]. Crawl data from real estate websites consist of point data of house prices. We used spatial interpolation to convert the point data into continuous surface data and calculated the mean values of the 300 m by 300 m grid cells.

3.4. Sentiment and Land Value Inequality Analysis. We spatially matched the sentiment scores with the land values to determine the unequal performance of different propensity sentiments on land of different values. This inequality curve is constructed similarly to the Lorenz curve. We plotted the cumulative proportion of land values on the horizontal axis and the cumulative proportion of positive sentiments on the vertical axis, starting with the evaluation unit with the lowest sentiment score. This curve is also known as a concentration curve. The farther the curve is from the line of equality, the higher the degree of sentiment inequality is and vice versa [64, 65]. The concentration index (CI) is the area under the concentration curve divided by the area under the diagonal. The CI of positive sentiments is defined as follows:

$$\mathrm{CI} = \frac{2}{Y_n}\sum_{i=1}^{n}(Y_i * R_i) - 1, \quad (2)$$

where CI is the concentration index of positive sentiments, Y_n is the mean value of the positive sentiments, and R_i is the i-th house price rank, which can be obtained by the following equation:

$$R_i = \frac{i - 0.5}{n}. \quad (3)$$

The CI ranges from -1 to 1. When $C \in (-1, 0)$, residents living in areas with a low land value have more positive sentiments, and when $C = -1$, the positive sentiments are observed in residents living in areas with the lowest land value. When $C \in (0, 1)$, residents living in areas with a high land value have more positive sentiments. When $C = 1$, positive sentiments are observed in residents living in areas with the highest land value. Thus, this index is a suitable indicator of sentiment and land value inequality.

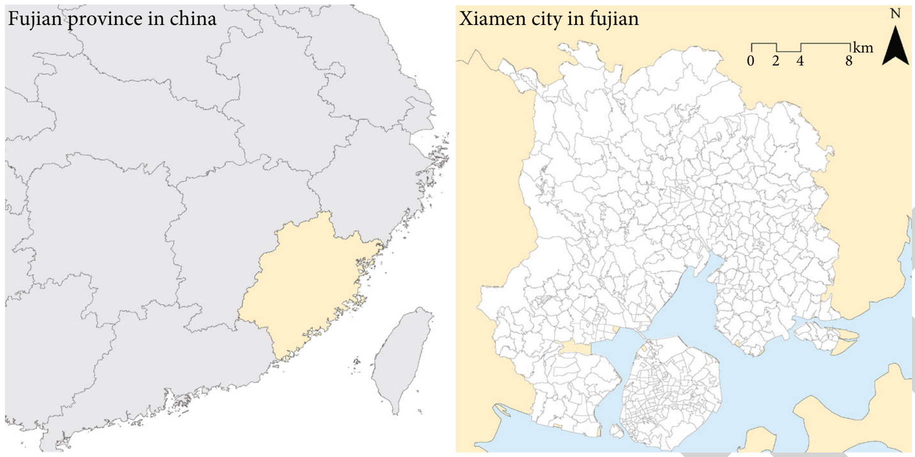


Figure 2: Study area.

4. Case Study

4.1. Study Area. The research area is Xiamen City, Fujian Province, China. Xiamen is located in East China, southeast of Fujian (Figure 2). There are 6 administrative regions under its jurisdiction, and the city area is 1699.39 square kilometers. According to the seventh census, Xiamen has a permanent population of 5.16 million. Geographically, Xiamen is divided into two regions: Xiamen Island is the original center of the city, outside of which new areas have developed.

Xiamen's GDP ranking in China is not high. However, due to its well-developed economy, beautiful environment, and livability, it has always ranked at the top of China's urban land value. Official data show that Xiamen's per capita GDP in 2020 was 123,600 yuan, ranking 21st in the country. However, due to land scarcity, the mean price of real estate in Xiamen has reached 51,476 yuan per square meter (official data from August 2020), ranking fourth in the country. Land values are unevenly distributed. The highest unit price in Xiamen Island is about 160,000 yuan, and the lowest unit price outside the island is about 4,000 yuan. Due to this large difference in land value in Xiamen, the development level differs substantially in different regions. The island is well developed, unlike the region outside of the island. Therefore, this study area is well suited to analyze the land value and residents' sentiments [66].

4.2. Data Sources

4.2.1. Social Media Data. The social media data used in this study were obtained from the Sina Weibo platform using a crawler. Sina Weibo is China's most well-known and most used social networking platform. Due to its broad national influence and numerous users, the tweet sample data are well suited for sentiment research [67–69]. We selected Weibo tweets within the Xiamen area during 2020. The data contains public information, such as tweet text, generation time, user ID, and location. A total of 460,000 sample data were preprocessed (Figure 3).

4.2.2. Urban Land Value Data. We used Python requests and bs4 modules to implement web crawlers to obtain information on public housing prices from the Xiamen Fangtianxia website (https://xm.fang.com/) as land value data. The request module was used to send and respond to network requests, and the bs4 module was used to parse the web pages [70, 71]. A total of 5,756 housing prices were obtained from the Xiamen Fangtianxia website. Each piece of information included the community's name, construction age, address, unit price, and rent. Only the unit price and geographic location were retained.

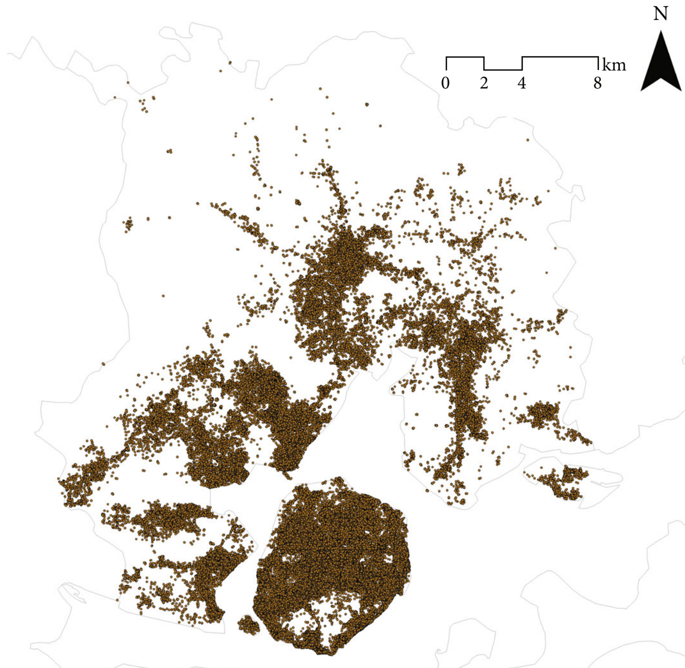
4.2.3. Urban Land Use Data. The land-use data were obtained from the 2020 Xiamen City Urban Land Classification Status Map created by the Xiamen Municipal Planning Bureau. Eight land-use types were used: administration and public services (A), business facilities (B), green space (G), manufacturing (M), nonconstruction land (N), residential (R), utility (U), and warehouse (W) [72]. The land value and land use distribution in Xiamen are shown in Figure 4.

4.3. Results

4.3.1. Spatial Differences in Urban Sentiments. The spatial differences in urban sentiments in Xiamen are shown in Figure 5. The positive sentiments are high in Xiamen Island, whereas the distribution of positive sentiments differs outside the island. Positive sentiments with high scores occur on the coast and near Xiamen Island, whereas there are fewer positive sentiments with a high score in the border areas far from the island. A comparison of Figures 5(a) and 5(b) indicates that the land values are generally higher in Xiamen Island and the western and northern coastal areas closest to the island, and the positive sentiment scores are also higher.

4.3.2. Sentiment Inequality in the City

(1) Relationship between Sentiment Inequality and Land Value at the Urban Scale. The inequality curve is shown in Figure 6. The cumulative line of positive sentiment is below



(a) Spatial distribution of Weibo data

No.	Weibo text	Generation time	Sentiment score
1	It's nice to see the night view~	2020.1.16	0.7865
2	There are some things that you don't realize are mistakes until you are more sober···	2020.3.5	0.3426
3	14 miles round trip is exhausting. I need more practice.	2020.4.15	0.4633
4	Life is funny if you know how to laugh at it.	2020.6.3	0.8027
5	Tooth extraction is very very very painful, ah! ! !	2020.9.25	0.1302
6	Happy birthday to me, have a great day! ! oye! !	2020.11.2	0.9411

(b) Text examples and analysis of the score

Figure 3: Spatial distribution of Weibo data and text examples and analysis of the score.

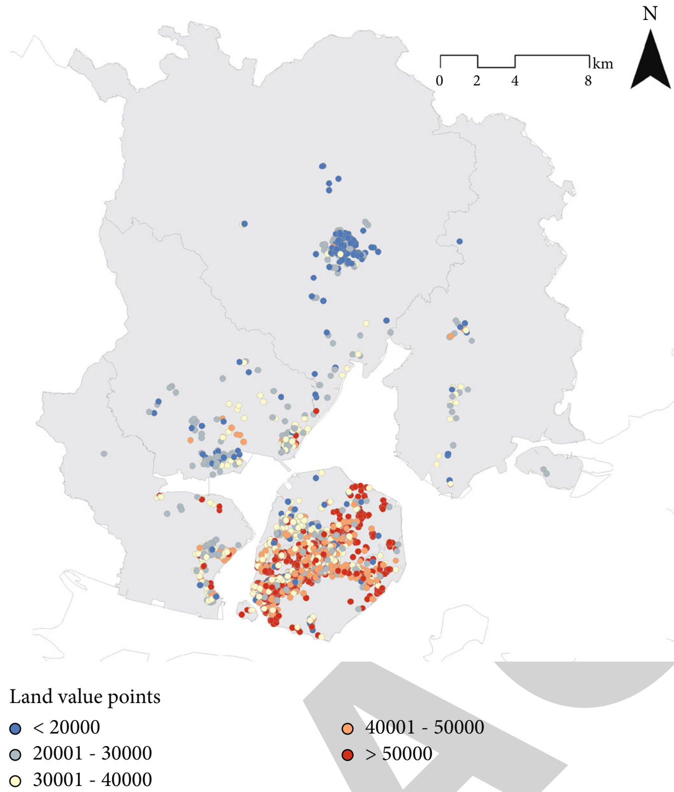
the line of equality, and the CI value is 0.07. This result indicates that sentiment inequality is caused by the high land value in the urban area and that higher positive sentiments are associated with higher land values (Table 1).

(2) Relationship between Sentiment Inequality and Land Value for Different Land-Use Types. We evaluated the relationship between sentiment inequality and land value for different urban land-use types and calculated the correlation between positive sentiments and land value, as well as the land value and sentiment inequality index (Table 1). A significant correlation occurs between positive sentiments and land value for the land-use types A, B, G, R, M, and N, indicating significant sentiment inequality. The cumulative curves of positive sentiments with high correlations of A, B, G, and R are lower than the line of equality (Figure 7). The relationship is not significant for the other types.

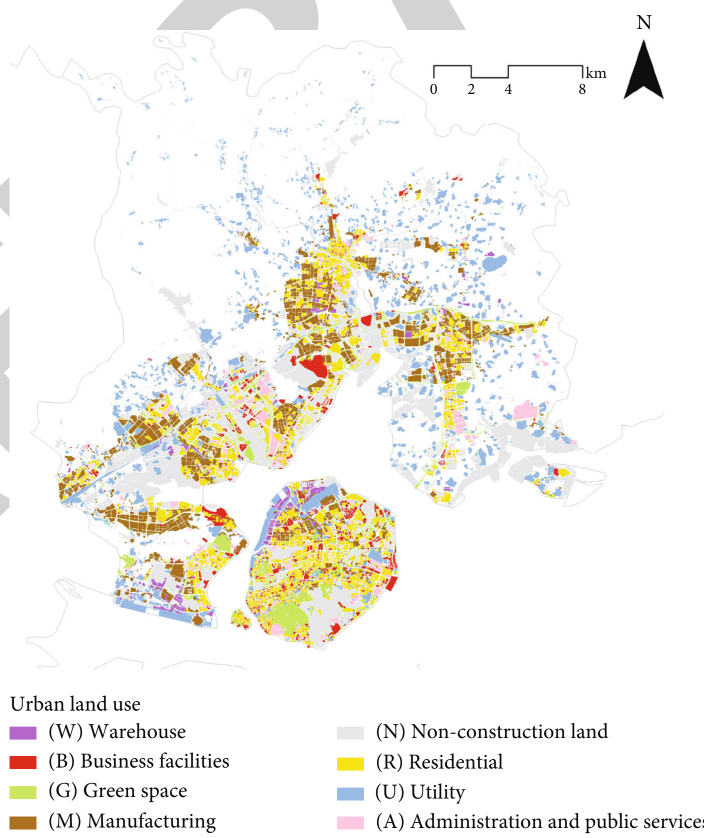
We conducted a classification of some subcategories of the A, B, and R land-use types to evaluate the sentiment inequality caused by the clustering of facilities and different housing property rights. The data were divided into Ac (culture, education, sports, and medical facilities), B1 (commercial service), B2 (business), B3 (entertainment), Rr (urban residential land), and Rv (urban village). It is worth noting that "urban village" is a heterogeneous environment that started to develop in many urban fringes in China at the beginning of 1990s. It typically occurs in low-income communities that provide low-cost housing for urban migrants. The correlation results are listed in Table 2.

5. Discussion

5.1. Advantages of Using Social Media Data to Analyze Public Sentiment. The widespread use of social media and big data provides an opportunity to study the relationship between sentiment and land value inequality. An analysis of the Weibo text data provides perceptions of the spatial environment for different regions and groups. If limited information is used, the sentiment evaluation may be subjective and based on individual experience, cognitive tendencies, sentiment state, and environment. Most studies used

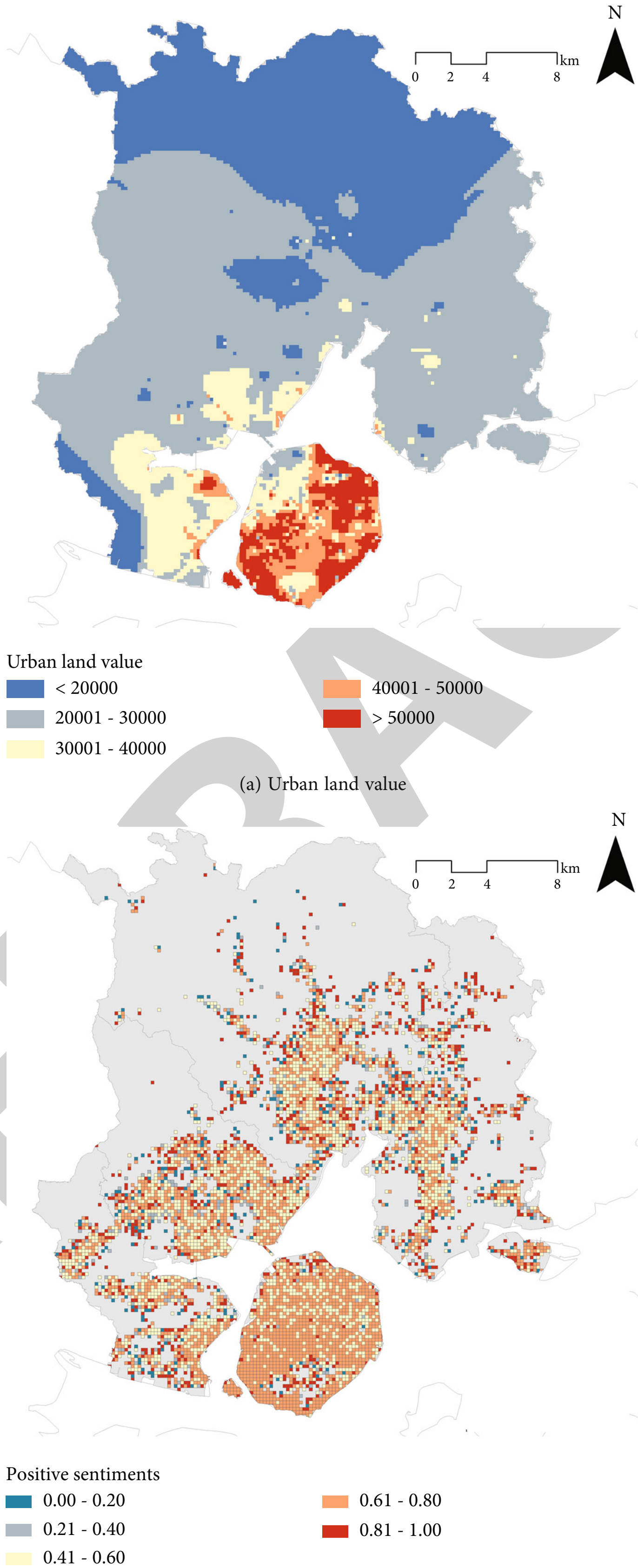


(a) Urban land value



(b) Urban land use

FIGURE 4: Urban land value and urban land use.



(a) Urban land value

(b) Positive sentiment

FIGURE 5: The spatial differences in urban sentiments.

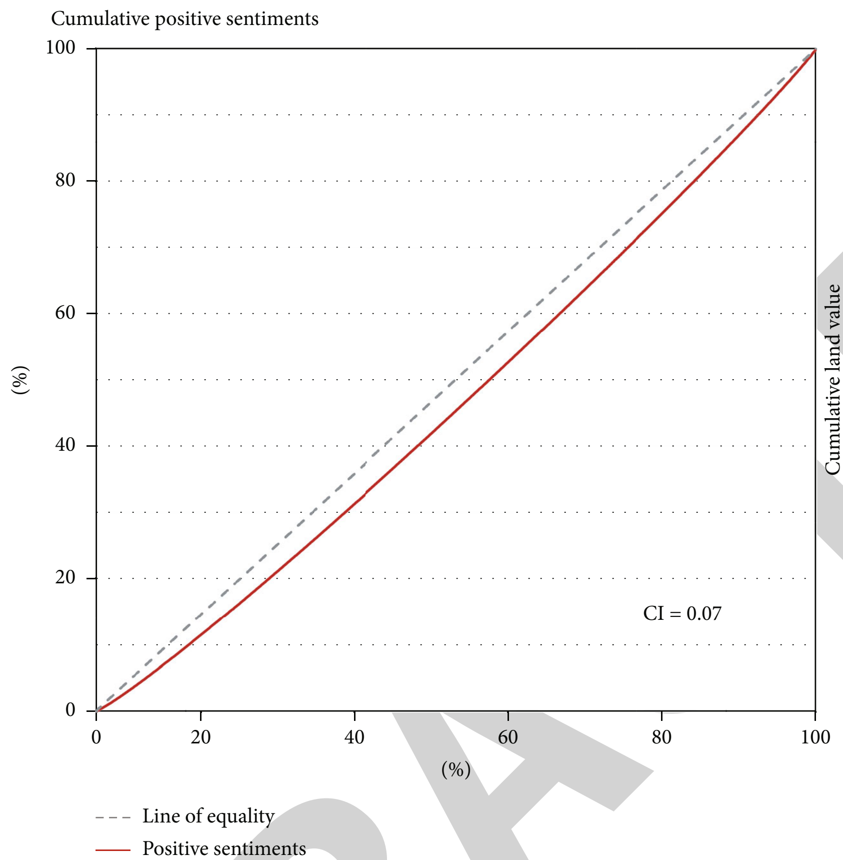


Figure 6: Inequality curve of cumulative positive sentiments and land value.

Table 1: The correlation between positive sentiments and land value for different land-use types.

Land use	A	B	G	R	M	U	W	N	Citywide
Adjusted R^2	0.242**	0.193**	0.241**	0.220**	0.109**	-0.161	0.172	0.111**	0.201**
N	291	186	400	1199	660	47	57	513	3353
Mean	0.6089	0.6301	0.6190	0.6101	0.5929	0.6042	0.6093	0.6003	0.6071

**Correlations are significant at the 0.01 level (two-tailed).

questionnaires, and some questions and the questionnaire introduction may affect the responses of the participants. Traditional discrete data also do not adequately represent the cumulative growth trend and the residents' sentiment inequality. In contrast, the use of big data is more objective and reflects the perception of various groups. Social media platforms not only provide a large amount of data but also greatly simplify data processing through data customization and filtering. The sentiment analysis platform can process massive text data efficiently and accurately. This method enables real-time interaction between online platforms and is applicable to various intelligent and information-based data platforms. The use of deep learning has transformed sentiment analysis from qualitative to quantitative research. The depth and accuracy of deep learning have refined sentiment analysis, and its comprehensiveness and accuracy have been improved by sentiment dictionaries, supervised learning, and semisupervised learning [73].

Therefore, using big data and sentiment analysis based on deep learning has increased the reliability of analyzing the relationship between sentiments with spatial attributes and land value inequality. This approach also reveals the complex impact pathways of the effects of urban social space deprivation on human health. The fusion of social media data and other intelligent platform data allows for global research and real-time online analysis. This approach also enables multidisciplinary urban research and provides large-scale, multidimensional data support for urban planning.

5.2. Relationship between Sentiment and High Land Value in Xiamen. Figures 5 and 6 show that positive sentiments are associated with high land values. The land value and the mean value of positive sentiments are generally higher in Xiamen Island than outside this area. A similar phenomenon also exists near the western and northern coast of

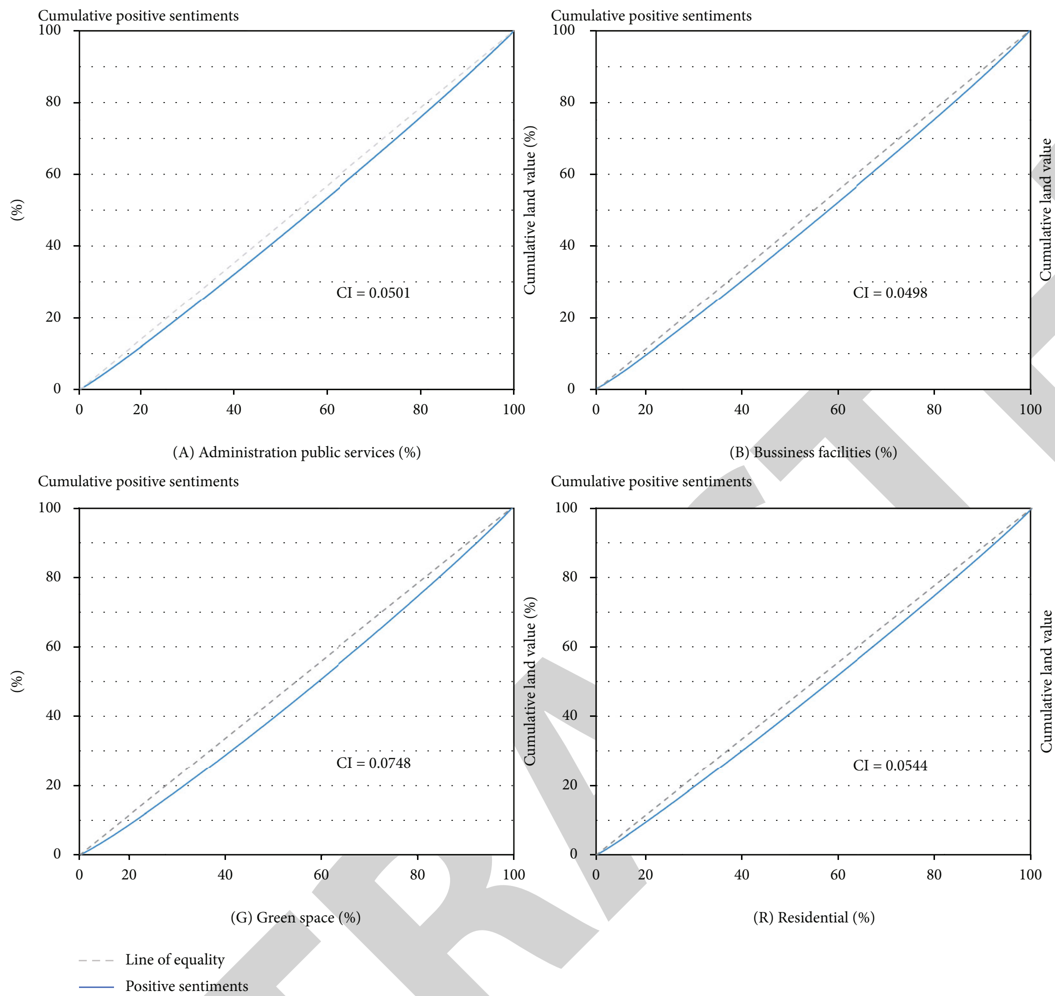


Figure 7: Sentiment inequalities for different land-use types in the city.

Table 2: The correlation between positive sentiment and land value for clustering of facilities.

Land use	Ac	B1	B2	B3	Rr	Rv
Adjust R^2	0.238**	0.151	0.327*	0.323*	0.250**	0.091
N	263	113	49	22	667	532
Mean	0.6083	0.6361	0.6155	0.6271	0.6193	0.5986

**Correlations are significant at the 0.01 level (two-tailed) and ∗correlations are significant at the 0.05 level (two-tailed).

Xiamen Island. On the other hand, the mean of the positive sentiment is lower in areas with lower land values in the outer urban fringe areas of Xiamen Island. The inequality curve, correlation results, and concentration analysis results indicate that the cumulative curve of positive sentiments is below the line of equality. This result shows that residents in high-value land areas have higher scores of positive sentiments and vice versa. The better environment and living conditions in areas with a high land value compensate for the pressure associated in these areas [74].

This study quantified sentiments derived from tweet data to evaluate urban sentiment and land value inequality for different land types. Table 1 indicates a strong positive correlation between the land value and positive sentiments for the A, B, G, and R land-use types. We believe that the reason may be that high land values have several advantages, such as a better living environment, a higher greening rate, and better road accessibility. High land values provide residents with better landscaping and greenery, higher investment in living facilities, and more leisure and recreational facilities, promoting positive sentiments. However, the correlation between sentiment and land value was low for the other land-use types. It is possible that these types are mainly used for work and production, and people experience similar environments and activities with a smaller focus on the environment; thus, there is less sentiment inequality.

It is observed in Table 2 that the positive sentiments in the Ac land are highly correlated with the land value. Land provides important life services, indicating that the higher the land value and the more aggregated the facilities, the better service they can provide. Among commercial gathering facilities, B2 and B3 are more likely to affect residents' positive sentiments due to facility clustering, while B1 has a higher average positive sentiment but is less affected by facility clustering. The land-use comparison between Rr and Rv indicates that the residents' positive sentiment is higher for urban residential land than for urban village land due to the higher land value. The sentiment of residents in urban village land is negligibly affected by the land value.

5.3. Policy Recommendations and Research Limitations. The land value of Xiamen promotes the positive sentiments of residents. However, from the perspective of sentiment spatial distribution, positive sentiments are widespread in Xiamen Island, unlike in the vast areas outside the island. Areas outside the island, especially areas closer to the coastline, have high development potential and value and should be considered in future planning. These areas can also alleviate the pressure of high-density population on Xiamen Island, increasing the land value outside of the island to promote positive sentiments among residents. Increasing the proportion of land use with a significant impact on positive sentiments, such as green space, public service, and management land, is also a major direction for old city renovation in the island and other areas with high land value. In addition, off-island development not only relieves the pressure on the island and expands the development area of the city center but also promotes coordinated development with surrounding cities. Off-island development can promote the interaction of industries and transportation between Xiamen and the surrounding cities and construction in areas with low land values. This policy can promote off-island development and increase land values, ultimately boosting positive sentiment among residents [75].

There are some limitations to this research method. First, in a grid with mixed land use, a larger grid size may filter out some smaller land-use types, resulting in missing samples. Further fine-grained research could determine the underlying reasons behind the differences in sentiment inequality in different regions. However, it is worth noting that people are more willing to post positive than negative sentiments on social media [76]. In the future, we will consider this influencing factor in more in-depth research to improve the reliability of the results. In addition, multidimensional and multiscale analysis using an integrated intelligent analysis platform will be a focus of future research to investigate the effect of multidimensional spatial factors on residents' sentiments.

6. Conclusion

This paper proposed a method to quantify human sentiments from social media tweet data using deep learning. Xiamen was used as an example to explore the relationship between sentiments and land value inequality. The results indicated sentiment inequality in Xiamen. At the city level, residents in high land value areas showed more positive sentiments. Residents were more affected by high land values in the G, R, N, and U land-use types, whereas the relationship between sentiments and land value was not significant for the other land-use types. Our research demonstrates that high land values have a positive impact on residents' sentiments. Urban residents show more positive sentiments toward living and leisure environments in areas with high land values (such as on Xiamen Island). The content of urban residents' social media tweets indicates that the positive effects of high land value, such as an improved living environment and better quality of life, outweigh the negative effects of a high cost of living.

The proposed sentiment analysis method based on social media big data and deep learning provides a new approach for analyzing urban sentiment and land value inequality. Utilizing intelligent deep learning algorithms and social media platforms provides a more objective approach to evaluating sentiments. The wide application of big data and sentiment analysis based on deep learning has transformed sentiment analysis from a subjective approach to an objective method to determine urban residents' perception of the spatial environment. In future research, multifactor decomposition of sentiment inequality will provide more in-depth information, and various influencing factors, such as the social structure, income differences, and education levels, will be included. Since the correlation results and significance of the data are affected by the research scale, the degree of sentiment inequality should also be investigated in the future. Targeted reduction of sentiment inequality is a focus of government workers. In conclusion, quantifying sentiments using social media tweets provides a more intuitive and convenient method for decision-makers in public health and urban planning to obtain public feedback, representing a feasible and valuable framework for the integration of multiplatform data.

Data Availability

The data used in this article is the Weibo data of Xiamen, China in 2020. The Weibo data used to support the findings of this study were supplied by Sina Weibo Platform under license and so cannot be made freely available. Requests for access to these data should be made to https://open.weibo.com/.

Conflicts of Interest

The authors declare no conflicts of interest.

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