Research Paper

A comparative Study of Residents' Emotions before and after the Period of the COVID-19 Epidemic Lockdown Based on Deep Learning

Take the main urban area of Harbin for example

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Abstract

The Corona Virus Disease 2019（COVID-19） is a public health emergency affecting all of humanity, and governments have taken different levels of lockdown measures to contain the spread of the epidemic. During this period, the daily travel activities of the population were restricted and negative feelings of the residents increased dramatically. Interestingly, there is a tendency for residents' sentiment and willingness to travel to rebound after the lifting of the lockdown, which may be due to a number of reasons, including the resilience of the urban space and its attractiveness to residents. In this paper, by crawling the WeiBo check-in data of the main city of Harbin in three different periods before the outbreak, during the epidemic closure period and at the beginning of the unsealing period, we use deep learning methods to identify residents' sentiment values based on the Baidu PaddleHub-ERNIE fine-tuned Chinese sentiment analysis model, compare and study the change characteristics of the sentiment points and sentiment values of the main city in the three time periods, and construct an "resilience" evaluation system of urban space The study found that after the closure of the epidemic, there was a tendency for residents' emotion points and emotion values to rebound with retaliation, and the spatial "resilience" of green space and historical and cultural district was stronger. We hope to provide some thoughts and insights for paying attention to residents' mental health and enhancing urban resilience in response to public health events.

Keywords

Corona Virus Disease 2019 (COVID-19); The Lockdown; Fluctuation of Emotion;
Deep Learning (DL); Evaluation of Resilience

1. Introduction

Since the outbreak of the Corona Virus Disease 2019, a major public health event, scholars in the field of urban planning at home and abroad have coincidentally increased their emphasis on building healthy cities, and the study of residents' subjective emotions has been a growing research direction in studies related to healthy cities. Early studies on mental health at home and abroad focused on negative psychology - that is, on the psychology of people in pathological or unhealthy states. With the growing research in the field of subjective well-being led by psychologist Diener (Diener, 2009), positive psychology has gradually developed into a vibrant new direction for mental health research, and more and more researchers are now using subjective well-being as an important indicator of mental health status. For example, Winzer Regina et al. (Winzer, 2021) argued that promoting well-being should be the main goal of mental health. The study of "well-being" originated from the concept of "quality of life" proposed by John Kenneth Galbraith(Galbraith, 1958). Based on this, psychology defines happiness as a subjective emotional judgment of positive or negative emotions in the human brain about external things (Zhanjun Xing, 2002). Therefore, it is important to identify residents' emotions in order to measure their subjective well-being and investigate the factors influencing their mental health to build a "healthy city". In the period of epidemic control, residents' emotions show a group gathering of negative emotions(Cao, G, 2021), and it is important to plan for this reality from the perspective of urban planning and policy making.

This study takes the main city of Harbin as an example, based on the microblogging punch card text data in three different periods before the epidemic outbreak, during the epidemic closure period and at the beginning of the unsealing period, and uses a deep learning approach to identify and visualize the emotion perception of urban hotspots based on the Baidu PaddleHub-ERNIE fine-tuned Chinese sentiment analysis model. By comparing and studying the emotional fluctuations and changes of residents in urban hotspots during the three different periods, we explore the fluctuations of residents' travel intention before and after the epidemic and the mitigating effect of urban spaces on negative emotions.

2. Current status of research and research methodology

2.1. Current status of research

For example, Florida (2013) found that the rational planning and layout of various indicators (population density, commercial layout, neighborhood space, ecological environment, and road traffic) under the neighborhood dimension is important for enhancing residents' well-being(Rentfrow, 2009). Seresinhe and Preis found a correlation between urban green space coverage, urban environmental aesthetics and residents' psychological well-being, using data from the England and Wales Census Citizen's Report on Health and a 'landscape' rating of geotagged photographs in the UK(Seresinhe, 2015). However, in the new context of the outbreak of the Newcastle pneumonia epidemic, which was a major public health event, and the new situation of the epidemic closure period, which restricted people's travel and brought obvious emotional impact to residents, there is a lack of studies that use the epidemic closure period as an entry point to comprehensively compare and analyze the relationship between urban hotspots and emotions before and after the epidemic. Nowadays, a growing number of studies corroborate the gradual deterioration of residents' mental health and well-being during the epidemic (Brodeur, 2021) (Davidlas, 2020) (de Oliveira, 2020), for example, Brodeur et al. found a significant increase in the frequency of Google search engine searches for "boredom" and "loneliness" in the first weeks of the blockade period in nine Western European countries [8]. The shift in residents' mood during the epidemic closure period also leads to a shift in their willingness to travel and behavioral activities, and the flow of people and residents' mood in urban hotspots may change as well. Therefore, it is necessary to compare and analyze the changes of pedestrian flow and residents' sentiment in urban hotspots spaces before and after the epidemic.

In terms of research methods, most scholars still use the traditional questionnaire and interview methods to obtain residents' subjective emotions, but in recent years, the advantages of massive big data sources for the breakthrough of traditional data quantity, the objectivity of extracting residents' behavioral activities, and the directness of obtaining emotional perceptions have been highlighted. At the level of emotion recognition, there are few studies in the field of urban planning using deep learning and natural language processing technology, especially in the study of residents' travel intention and behavioral activities through emotion recognition. This paper adopts the Baidu PaddleHub-ERNIE fine-tuned Chinese sentiment analysis model for sentiment recognition, which has two advantages over traditional machine learning: first, the model can make natural language adjustments to text data different from those in the training set to improve accuracy; second, its accuracy is continuously improved through repeated training and learning, and the average accuracy for sentiment polarity is above 85%. The accuracy average for emotional polarity is above 85%, and the accuracy average for emotion type is above 75%, and the accuracy average is higher than that of machine learning models such as support vector machines (Chauhan,2008).

2.2. Research Methodology

The data source of this study is microblog check-in data, and firstly, semantic analysis of the microblog text is performed for sentiment annotation. Based on deep learning algorithm, Baidu PaddleHub-ERNIE fine-tuned Chinese sentiment analysis model is used for sentiment identification, and QGIS software is used to spatially drop the data results, to compare and analyze the spatial distribution of sentiment points and sentiment values in the main city of Harbin in three different periods, and to construct an urban spatial "toughness The spatial "resilience" model was constructed to analyze and evaluate the changes of residents' travel activities and spatial emotions in each period.

3. Data acquisition and processing

3.1. Data Acquisition

The main city of Harbin is located in the western part of Harbin city area (see Figure 1), and this study uses the main city of Harbin (excluding Hulan district) as the study area (see Figure 2), and uses a large text-based social networking website - Weibo as the data source, which has the advantages of breaking through the quantitative limitations of traditional data, reducing The advantages of this data source compared with traditional data sources such as questionnaires (interviews) include: breaking the quantitative limitation of traditional data, reducing the interference factors of questionnaire-interview survey method, and reducing the inaccuracy of retrospective interviews. Based on the realistic closure of the Harbin epidemic in 2020, the author selected three different periods before the outbreak, during the epidemic closure period and at the beginning of the unsealing period for comparison and analysis, and removed the periods of the surge in the number of trips on holidays such as May Day and November. It was finally determined to crawl a total of 103,450 text data with punch card positioning in Harbin City from March 1, 2018 to April 30, 2018, January 23, 2020 to March 23, 2020, and May 18, 2020 to July 18, 2020, involving 5896 location positioning. The obtained structured data contained information such as user ID, microblog body, posting location, topic, number of retweets, comments, likes, and posting time (see Table 1).

Figure 1 Location of the main city of Harbin in the city limits

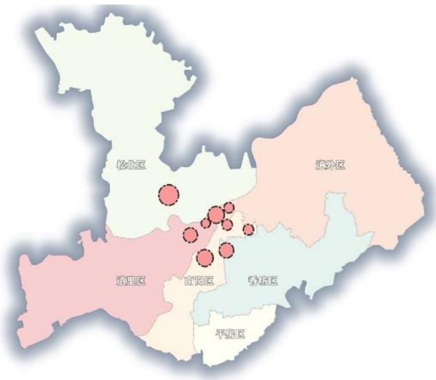

Figure 2 Scope of the study in this paper

Table 1 Structured text of microblogging text data data

User nickname	Body of the tweet	Posting Location	Topics	Number of Retweets	Number of comments	Number of Likes	Release Time
多味 Chacha	加油哈尔滨！还是喜欢看你的人流如织，车水马龙的喧闹！	哈尔滨·圣索菲亚大教堂	2020 你好	1	0	1	2020/2/24 23:34:00

3.2 Data pre-processing

This study aims to compare the travel intentions and emotions of Harbin residents in the three time periods before the epidemic, during the closure period and at the beginning of the unsealing period, so to ensure the authenticity and availability of the location data, the locations obtained were screened: firstly, the check-in locations containing "Harbin" but belonging to other cities were screened out. First, filter out the check-in locations that contain "Harbin" but belong to other cities. Then, some of the data that could not be obtained by latitude and longitude because the address was not detailed were cleared (e.g., nearly 30,000 pieces of data with "Harbin" as the check-in location). Finally, the QGIS software was used to remove the data from the check-in locations that were not in the main city of Harbin, but in the surrounding cities and counties.

Next, the text data are processed: first, the text information that cannot express users' subjective emotions, such as advertising tweets that do not have subjective opinions, invalid tweets used to brush data to hit the list, and other data are deleted. Then, we used the tool of deleting duplicate items in Excel to keep only one corresponding text data. After the above data screening, we finally obtained a total of 18256 data in three time periods, which will be referred to as the dataset below for the convenience of description.

3.3 Text Emotion Recognition

3.3.1 Semantic analysis of text

In order to improve the accuracy of subsequent sentiment recognition, the author preprocessed the microblog text data before recognition, mainly including the following two parts: 1. The study is based on the deactivation of words in HIT. In this study, the text data were deactivated based on the deactivation word list of HIT, the deactivation word list of Baidu, and the deactivation word list of Chinese. 2. word separation, this study used the lexical analysis tool LAC to separate the text training set. In addition, invalid symbols such as "@user", "#topic", "share image", etc. were also filtered and removed in the pre-processing stage to avoid affecting the accuracy of the final results (see Table 2). (see Table 2).

Table 2 Example of data after processing (deactivation and splitting of words)

Original microblog text data	Example of unified text data format after pre-processing
难受感冒了，昨天还崴脚来哈尔滨得时候就特别压抑够了，每次走的时候都说不想再来了	难受 感冒 昨天 崴脚 哈尔滨 时候 压抑 够了 每次 走 说 不 想 再来
山川湖海柴米田园你若是爱对了人怎样都是好日子#夏梦尼花艺##哈尔滨花店##哈尔滨花艺培训##哈尔滨花艺沙龙#	山川湖海柴米田园 爱 对 都是 好日子
🌿给自己一份自信，不浮、不躁；给自己一份洒脱，静静思，淡淡行，无论何时何地，做简单真实的自己。早安☀️#哈尔滨##哈尔滨生活#	一份 自信 不浮 不躁 一份 洒脱 静静思 淡淡 行 简单 真实

3.3.2 Emotion recognition model construction

The mainstream domestic deep learning-based emotion recognition models are mainly ERNIE (Enhanced Representation through kNowledge IntEgration) and BERT (Bidirectional Encoder Representation from Transformers), ERNIE is an enhanced model that can be enhanced by continuous learning of semantic representation proposed by Baidu, and its validation on various Chinese tasks of natural language processing (NLP) such as language inference, semantic similarity, named entity recognition, sentiment analysis, question and answer matching, etc. shows that the model effect surpasses BERT across the board (Sun, Y, 2019) (see Table 3).

Table 3 Comparison of the accuracy of ERNIE and BERT models

	ERNIE tiny, Chinese	BERT-Base, Chinese
Emotional Polarity	87%	83%
Emotional Categories	79%	75%

In the existing emotion recognition analysis, emotions are mostly measured by positive and negative polarities, while ignoring that some text data do not have obvious emotional directionality. To ensure the homogeneity and accuracy of the sample, this study locates 3000 text data in the training set, including 1000 texts of positive emotion, neutral and negative emotion each, and annotates the training set texts by manual labeling. In addition, for a further analysis of spatial emotion distribution and residents' willingness to travel, the author combined Baidu training and the emotion classification of domestic and foreign scholars, through Frijda's proposed behavioral tendencies and facing events corresponding to the corresponding emotions (Frijda, 1987) (see Table 4), and finally identified excitement, delight, expectation, no feeling (sexless), sadness, anger, and anxiety, but in the process of identifying the training set, there were only 96 data for excitement and 38 data for anger, so the final determination was five types of emotions: joy, anticipation, senselessness, sadness, and anxiety. Among them, joy and anticipation correspond to positive emotions, while sadness and anxiety correspond to negative emotions. In particular, it should be noted that the emotion recognition model is a process of judging emotions through training and indirectly, and it is easier to recognize emotions with high emotional intensity, while text expressions with lower intensity will be recognized as no-sense i.e. neutral emotions. In this study, we focus on the fluctuation and change of strong emotions in each space, so we remove the texts with "no emotion" in the analysis of dominant emotions in each space.

Table 4 Behavior-emotion correspondence table proposed by Frijda

Facing time or behavioral tendencies	Emotion Type
Events beyond their control or circumstances normally beyond their control.	Fear Anxiety
Uncertainty about whether you can cope can induce avoidance.	
Unexpected but controllable events, especially self-fulfilling	Happiness Joy
and things that enhance self-esteem	
Unpleasant events occur	(of life) be difficult
Unpleasant and uncontrollable events	Anger
Something that has not actually happened and will not happen for some time	Insensitivity Indifference
Controllable events that can dominate and control others	Excitement Excitement
Events that are beyond your control and that will lead to uncertainty in your next actions	Anxiety Despair

4 Comparative analysis of mood points and mood values in the main city

4.1 Comparative analysis of three different periods of emotional points

The microblogging check-in punching places reflect the main activity locations and hotspot spaces of residents in the main city of Harbin, and this study measures the number of check-ins at the punching places to measure the flow of people in the place. After the location screening process, the number of check-ins within the study area for three different periods is as follows (see Table 5). It can be seen that the check-in data decreased significantly during the closure period in 2020 to less than 40% of the pre-epidemic period, while the foot traffic quickly rebounded to more than twice the closure period at the beginning of the unclosure, but decreased by 15% compared to the pre-epidemic outbreak.

Table 5 Number of check-ins in different periods

Time	Emotional points (bars)
20180301-20180430	8978
20200123-20200323	3421
20200506-20200706	7359

Next, a more intuitive comparative analysis can be made by using Qgis software to draw a heat map of pedestrian flow in the main city based on the number of check-ins (Figure 456). First, by comparing the heat map of human flow before the outbreak and the initial period of unsealing, we can see that the former check-in locations are more scattered, and the areas with dense human flow are more numerous and scattered. The most crowded places are the traffic hub places - the area belonging to Harbin Taiping International Airport; the latter check-in places have a more obvious tendency to gather in the central area of the city, and the most crowded places are Central Street shopping area, Aijian shopping area and Taiping International Airport. Secondly, comparing the period of closure and the early period of unsealing, the former shows a lower level of traffic flow in the main city, and the traffic flow inside the Inner Ring Road is still slightly higher than that outside the Inner Ring Road, but the central aggregation is relatively less obvious, and the highest traffic flow is still at Taiping International Airport; the latter has a very obvious central aggregation, and the traffic flow in the city center is obviously more than that outside the Inner Ring Road, and the distribution is more extensive. Next, the check-in data were categorized and summarized by location, and the hotspots in the three different periods were ranked according to the number of check-ins. It was found that the number of check-ins at the top 10 check-in locations in the pre-epidemic period accounted for 21% of the total number of check-ins, and the top 10 locations in order were: Qunli, Shangzhi Street, Central Street, Harbin Taiping International Airport, Haxi Street District, Innovation Street, Hanshui Road, Heilongjiang University, Jing Yu Street, Gu Xiang Street; the top 10 check-in locations during the epidemic closure period accounted for 14% of the total check-ins, with the top 10 locations ranked in order: Qunli,

Aijian Community, Central Street, Garden Street, Harbin Taiping International Airport, Aijian Binjiang International Community, Harbin West Station, Olive City, Yongji Home and Hulan University City; the top 10 check-in locations at the beginning of the unsealing period had as many as 32% of the total check-in times, and the top 10 locations in order were: Central Street, Qunli, Harbin Ice and Snow World, Harbin Taiping International Airport, Aijian Community, Garden Street, St. Sophia Cathedral, Heilongjiang University, China Snow Valley Scenic Area and Harbin West Station.

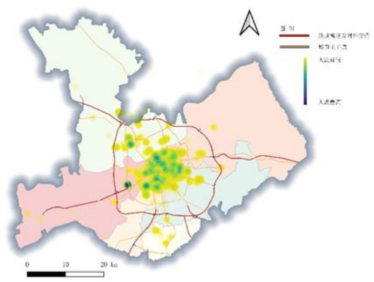

Figure 3 Distribution of sentiment points before the outbreak

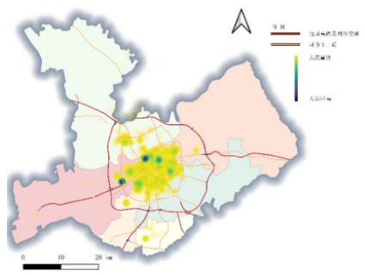

Figure 4 Distribution of emotional points during the epidemic closure and control period

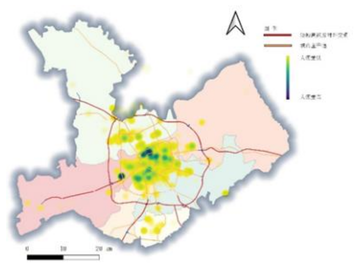

Figure 5 Distribution of unblocked pre-sentiment points

4.2 Comparative analysis of emotional polarity in three different periods

In this study, emotional polarity was divided into three categories: positive, neutral, and negative, and the percentages of each type of emotion in different periods were as follows (see Table 6). Based on the results obtained from the emotion recognition model, positive emotion is defined as 1, neutral is defined as 0, and negative emotion is defined as -1. Each check-in place is scored and the average value of emotion within each location is calculated, and the score is between -1 and 1. The higher the score is, the more positive the user's emotion at that place is, and vice versa, the more negative. Based on the table below, we can see that the positive sentiment in the main city during the 2020 closure period decreased significantly compared to the initial period of the epidemic, by 27%; at the same time, the percentage of positive sentiment in the initial period of the lifting of the closure quickly rebounded to the level of the closure period, and increased by 8% compared to the closure period. At the same time, the neutral sentiment at the beginning of the three epidemics was relatively flat compared to the closure period, while the neutral sentiment at the beginning of the declosure period decreased by 3%, and the negative sentiment share in that period also reached an extremely low level of 7%.

Table 6 Percentage of emotional polarity in different periods

Time	Percentage of positive sentiment	Neutral Sentiment Ratio	Percentage of negative emotions
20180301-20180501	0.4224	0.4588	0.1188
20200123-20200323	0.1493	0.4573	0.3934
20200506-20200706	0.5048	0.4252	0.0700

The distribution of emotional polarity in hotspot space was made by QGIS software, and five levels were divided in the -1-1 score interval and given corresponding color blocks to unify the intensity of emotional polarity represented by the emotional polarity color blocks in three periods, which can more intuitively compare the spatial distribution of residents' emotions in three periods (Figure 789). First, by comparing the emotional polarity before the outbreak and at the beginning of the unsealing period, we can see that the former has more scattered check-in locations and a smaller and more dispersed share of positive emotions than the latter, while the latter has a significantly higher share of positive emotions and is clustered in the central area of the city. Interestingly, the former's negative emotions were also concentrated in the city center, and the "love and hate" situation appeared in the city center in both periods, while the former's strong positive emotions accounted for a very low percentage.

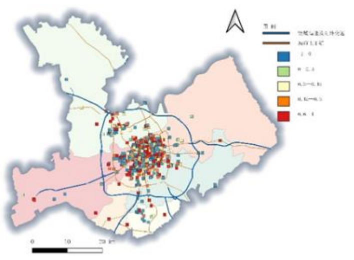

Figure 6 Distribution of emotional polarity before the outbreak

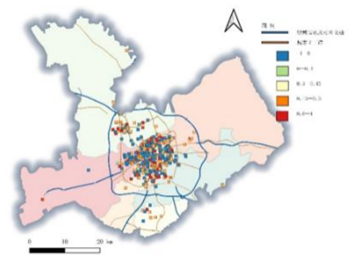

Figure 7 Distribution of emotional polarity during the outbreak closure period

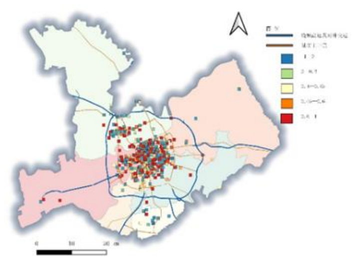

Figure 8 Distribution of emotional polarity at the beginning of unblocking

4.3 Comparative analysis of three different periods of emotional types

Based on the above classification of emotions, the five emotion types of joy, anticipation, no-sense, sadness, and anxiety were defined as 1, 2, 3, 4, and 5, respectively, and the data obtained based on the emotion recognition model were processed. Based on the volatility and changes of strong emotions mentioned in the previous section, we first remove the sign-in data of emotionless emotions, and then find the plural of emotion types of each sign-in location (i.e., the dominant emotion of the location), such as the total number of sign-ins in Aijian community before the epidemic is 187, of which the number of strong emotions is 112, and the number of anxiety emotions is 53 and the largest proportion of strong emotions, then anxiety emotion is the dominant emotion of Aijian community. The dominant emotion of the community is anxiety. Based on this, we finally got the dominant emotions in three different periods (see Table 7), we can see that before the epidemic and at the beginning of the unsealing period, joyful emotions accounted for more than 60%, and the early period of unsealing was about two percentage points higher than before the epidemic; in the period of 2020, anxiety accounted for much higher than other periods, reaching more than 45%, and the total percentage of sadness and anxiety reached 64%, and the expectation in this period was 7% higher than that of joyful emotions. accounted for about 7% higher than the share of joyful emotions, which is very different from the other two periods.

Table 7 Percentage of dominant emotions in different periods

Time	Percentage of joy	Expectation ratio	Difficulty in accounting for	Anxiety Ratio
20180301-20180501	0.6681	0.1834	0.0682	0.0803
20200123-20200323	0.1326	0.2189	0.1874	0.4581
20200506-20200706	0.6806	0.2341	0.0795	0.0650

The distribution of emotional polarity in the hotspot space was created by QGIS software, and the four strong emotion types were given different color blocks to help compare the distribution of dominant emotions in each space within the three periods (Figure 10 11 12). First, by comparing the polarity of emotions before the outbreak and at the beginning of the unsealing period, we can see that the distribution of strong emotions is more dispersed in the former period, and joyful emotions are less and more dispersed than in the latter period; in the latter period, the proportion of positive emotions increases significantly and is concentrated in the central part of the city. Secondly, comparing the period of closure and the early period of unsealing, the distribution of emotions in the former is more concentrated, and the dominant emotion in the former urban area is anxiety and concentrated in the central area of the city, while the proportion of joy in the former is very low.

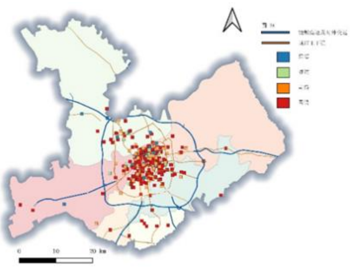

Figure 9 Distribution of mood types before the outbreak

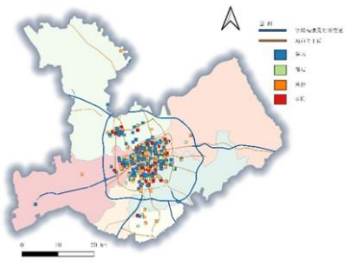

Figure 10 Distribution of the types of emotions during the epidemic closure period

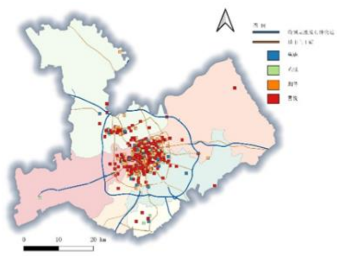

Figure 11 Distribution of emotional types at the beginning of unblocking

4.4 Evaluation of the "resilience" of urban space

4.4.1 The Degree of Arousal from External Stimuli

The degree of arousal of the external environment is the intensity of arousal of the resident's emotions by external pressure; the greater the intensity of arousal, the greater the external pressure, and the type of emotions resulting from this arousal is not necessarily negative (Reisenzein, 1994). It is noteworthy that for arousal of negative types of emotions external pressure is greater. However, due to the complexity of emotional arousal stimuli, the sources of external stress are not distinguished here, and the social and physical environments that may cause changes in mood are collectively referred to as the external environment. The correspondence between the external environment and the types of emotions is shown in Table 8.

Table 8 Correspondence between the degree of arousal in the external environment and the type of emotion

Emotional polarity + degree of arousal	Emotion Type
Positive emotions + high arousal	Delight
Positive emotion + Medium arousal degree	Hope
Low to medium wakefulness	Sexless
Negative emotion + Medium arousal degree	Sadness
Negative emotions + high arousal	Anxiety

4.4.2 Sensitivity to Negative Emotions (SNE)

Negative emotional sensitivity is the sensitivity of the urban emotional environment to various disturbances and reflects its ability to resist stimuli. When the negative emotional sensitivity of an area is lower, it proves that the area is more emotionally stable and safe. The essence of the emotional sensitivity assessment is that it is ideal, i.e., ignoring the personal evaluation of a few people, and analyzing the type and magnitude of the possibility of major emotional problems, the areas where they may occur and their extent by taking the mean value.

4.4.3 The degree of Emotional Recovery Rebounds (ERR)

Through the observation of the data, it was found that the average mood in most of the city always fluctuates up and down from a certain mean value, and emotional recovery resilience refers to the ability of the emotional environment to self-regulate and self-recover when internal or external disturbances or stresses do not exceed its elastic limit. Scholars Chauhan S et al. based on an empirical study found that the rebound of positive emotions after the Corona Virus Disease 2019 promotes an increase in the desire to buy for the apparel industry, which leads to an increase in impulse buying behavior (Chauhan, S, 2021). In this paper, we compare the activity patterns before the outbreak and at the early stage of the closure, and study the amount of change and recovery of emotional information before and after the closure period by classifying different spatial place types, and then determine the rebound degree of emotional recovery in different spatial places in Harbin city.

4.4.4 Evaluation of the "resilience" of urban space

The distribution of urban spatial "resilience" in the main urban area of Harbin can be obtained by superimposing the triple index method, and the overall urban spatial "resilience" in the main urban area of Harbin has the result that the center is more resilient and the peripheral areas outside the Third Ring Road are less resilient. For different types of spatial places, the spatial resilience of park space and historical and cultural districts is stronger, while the resilience of commercial and office areas is poorer. It is noteworthy that the external environmental arousal intensity is higher in commercial areas and the sensitivity to negative emotions is also higher, which indicates that the physical spatial environment is more influenced by the external pressure during the epidemic closure period.

5 Conclusion and reflection

The conclusions and reflections obtained from this study are as follows. Firstly, this paper mainly compares and analyzes the changes of pedestrian flow in the hotspot space before and after the epidemic, and empirically verifies the influence of the epidemic closure period on residents' travel intentions and behavioral activities, and confirms that the epidemic closure period greatly restricts residents' travel, and the residents' travel intentions increase at the early stage of unsealing, and the pedestrian flow basically reverts to the pre-epidemic level. Secondly, we found that negative emotions such as "sadness" and "anxiety" increased sharply during the period of epidemic closure, and the proportion of positive emotions was higher than that of joyful emotions. This indicates that there is a certain volatility and tendency of retaliatory rebound in residents' emotions before and after the epidemic. Third, the evaluation of the "resilience" of urban space shows that parks and green spaces play an important role in enhancing the resilience of cities in response to public health events. Finally, this study adopts a deep learning-based text emotion recognition model, and its recognition accuracy will be improved after repeated learning, which provides a new research and computational method for processing large amount of big data that cannot be achieved by human extraction calculation in urban research.

There are some limitations and shortcomings in this paper. First of all, the bias of the age of users due to the source of data; more than 75% of Weibo users are young people aged 18-30, which makes this study reflect only the change of emotional perception of this age group before and after the epidemic. At the same time, for example, the Aijian shopping district contains a large number of Aijian neighborhood residents who check in within this range will affect the judgment of such places "This is something that was not addressed in this study - the inability to control for interference from other types of functional areas within each place type.

This paper is an attempt and exploration of the processing of massive data based on deep learning technology for emotion recognition and placement in space, and the next should be based on the social development needs of the post-epidemic era, constantly improve the scientific nature of this process, in-depth theoretical research, in order to study the residents' emotions to build a "healthy city" and enhance urban resilience The next step is to improve the scientific process and deepen the theoretical research, so as to provide thoughts and inspiration for the study of residents' emotions to build "healthy cities" and enhance urban resilience.

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6 References

[1] Diener, E., Diener, M., & Diener, C. (2009). Factors predicting the subjective well-being of nations. in Culture and well-being (pp. 43-70). Springer, Dordrecht.

[2] Winzer, R., Vaez, M., Lindberg, L., & Sorjonen, K. (2021). Exploring associations between subjective well-being and personality over a time span of 15-18 months: a cohort study of adolescents in BMC psychology, 9(1), 1-10.

[3] Galbraith, J. K. (1998). The affluent society. Houghton Mifflin Harcourt.

[4] Zhanjun Xing. (2002). A review of research on subjective well-being measures. Psychological Science, 25(3), 336-338.

[5] Cao, G., Shen, L., Evans, R., Zhang, Z., Bi, Q., Huang, W., & Zhang, W. (2021). Analysis of social media data for public emotion on the Wuhan lockdown event during the COVID-19 pandemic. Computer Methods and Programs in Biomedicine, 212, 106468.

[6] Rentfrow, P. J., Mellander, C., & Florida, R. (2009). Happy states of America: A state-level analysis of psychological, economic, and social well-being. journal of Research in Personality, 43(6), 1073- 1082.

[7] Seresinhe, C. I., Preis, T., & Moat, H. S. (2015). Quantifying the impact of scenic environments on health. scientific reports, 5(1), 1-9.

[8] Brodeur, A., Clark, A. E., Fleche, S., & Powdthavee, N. (2020). Assessing the impact of the coronavirus lockdown on unhappiness, loneliness, and boredom using Google Trends. arXiv preprint arXiv:2004.12129.

[9] Jones, N. R., Qureshi, Z. U., Temple, R. J., Larwood, J. P., Greenhalgh, T., & Bourouiba, L. (2020). Two metres or one: what is the evidence for physical distancing in covide-19? bmj, 370.

[10] de Oliveira, L. A., & de Aguiar Arantes, R. (2020). Neighborhood effects and urban inequalities: the impact of Covid-19 on the periphery of Salvador, Brazil. city & Society (Washington , DC), 32(1).

[11] Chauhan, N. K., & Singh, K. (2018, September). A review on conventional machine learning vs deep learning. in 2018 International conference on computing, power and communication technologies (GUCON) (pp. 347-352). IEEE.

[12] Sun, Y., Wang, S., Li, Y., Feng, S., Chen, X., Zhang, H., ... & Wu, H. (2019). Ernie: Enhanced representation through knowledge integration. arXiv preprint arXiv:1904.09223.

[13] Frijda, N. H. (1987). Emotion, cognitive structure, and action tendency. cognition and emotion, 1(2), 115-143.

[14] Reisenzein, R. (1994). Pleasure-arousal theory and the intensity of emotions. journal of personality and social psychology, 67(3), 525.

[15] Chauhan, S., Banerjee, R., & Dagar, V. (2021). Analysis of Impulse Buying Behaviour of Consumer During COVID-19: An Empirical Study. Millennial Asia, 09763996211041215.