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Using Transfer Entropy and Data Mining to Analyze Climate Information Communication Flow in China

Meifen Wu¹, Ruyin Long^{2,*}, Jingwen Na^{2,*} and Wenbo Li³

¹ School of Economics and Management, Fuzhou University, Fuzhou 350108, China

² School of Business, Jiangnan University, Wuxi 214122, China

³ Business School, Jiangsu Normal University, Xuzhou 221116, China

* Correspondence: longruiyin@163.com (R.L.); najingwen2022@163.com (J.N.);
Tel.: +86-13952298058 (R.L.); +86-15109663335 (J.N.)

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Abstract: In the era of globalization and digitalization, this study employs transfer entropy and data mining to analyze climate information flows before and after China's dual-carbon target. The analysis is based on 904,837 posts collected from 2019 to November 2021, including 17,380 original posts, 767,171 first-layer retweets, and 120,286 second-layer retweets, and combines Latent Dirichlet Allocation (LDA) topic modeling, Bidirectional Encoder Representations from Transformers (BERT)-based emotion classification, information entropy, and transfer entropy. Results show a policy-driven topic shift from “climate reporting” to “carbon neutrality” following the policy announcement, accompanied by changes in the distribution of public emotions, including greater visibility of anger and sadness in some dissemination layers. Government and celebrities dominate agenda-setting, while emotional polarization among ordinary and talent users indicates hierarchical differences in aggregate emotional expression. During diffusion, emotional expression shifted from positive toward negative categories, a pattern that is consistent with an “emotional cycle effect”. Geographic differences were observed in climate-related posting activity and emotional expression. Information entropy differed across dissemination layers, indicating changes in the diversity and uncertainty of emotional distributions. These insights can inform more effective climate-policy communication and dissemination strategies.

Keywords: climate change; China; data mining; dual-carbon target; information communication flow

1. Introduction

Internet-based information technology and communication have transformed the way information is received, shortening the distance and time for information dissemination and enhancing its fluidity. To voice their thoughts and worries regarding complicated and well-known issues, people actively participate in these topics online [1,2]. Currently, people's worries about climate change are becoming more widespread and powerful as social media usage increases [3]. As a complex social phenomenon, the flow and exchange of information elements between regions and different information levels may affect individuals' perception and understanding of climate change. Prior research has demonstrated that information technology has a major effect on regional economy and spatial patterns through “information flow” [4]. Thus, given the history of the Internet's rapid development, the study of the flow of climate information is especially crucial.

Sina Weibo is one of China's leading social media platforms and has become a major channel for the dissemination and acquisition of public information [5]. Almost all information, especially hot events, will spread



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rapidly, which has a great impact on society. When Weibo's themes and emotions resonate with visitors, they will be forwarded, commented or praised, forming new content and emotions, which will further affect new visitors and produce a series of "butterfly effects". This impact on the public brought by information dissemination is vital for influencing people's comprehension and perception of climate change. The general concern about climate change among people can have two outcomes: essentially, it can have an impact on individual energy conservation and emission reduction [6,7]. Public concerns might put pressure on the government to strengthen environmental regulations, lessen information asymmetry, and encourage government action [8]. Prior studies on the diffusion of information have mostly concentrated on the attitudes, worries, and feelings of the public on social media platforms. For instance, Gong et al. [9] examined how the public views nuclear power and what worries, opinions, and attitudes are expressed on social media platforms. They also examined how the public perceives nuclear power, how information is disseminated, and how public concern is distributed geographically and spatially. Three factors were examined by Li et al. [10] while discussing the unique performance of social media users' involvement in crisis management: the discussion subject, the mood of users, and the manner of information transmission.

However, there is still an important feature of social media networks, which is flow [11]. According to interactive ceremony theory, a complete social interaction process usually consists of three parts: attention flow, emotion flow, and symbol flow. Attention flow refers to the process of consciousness flowing when people gather together to form a common focus of attention. Emotional flow refers to the flow of emotions and feelings that are aroused after people form a common focus of attention in the process of interaction. Symbol flow closely follows the trajectory of emotional flow, which indicates the flow mode of meaning symbols generated when people resonate with emotions. It is called "flow" because these three kinds of information units, which belong to the level of material symbols or spiritual consciousness, all present a fluid feature in the process of people's interaction [12]. This study defines the information communication flow of climate change, drawing from prior research, as the movement and circulation of digital content related to climate change among social media platform users. This includes the shifting of people's attention topics over time (referred to as attention flow), the shifting of people's overall attention and the appearance or disappearance of different user types (referred to as user flow), and people's emotional tendency to move between different information levels (referred to as emotional flow).

The three dimensions of climate information communication flow are theoretically connected. Interaction ritual theory explains how a shared focus of attention can organize user participation and emotional responses, while information diffusion theory explains how topics and emotions move across original-post and retweet layers. Emotional contagion further provides an interpretive lens for possible emotional amplification during dissemination. Within this framework, the announcement of China's dual-carbon target is regarded as a macro-level policy signal that may redirect public attention, alter the participation of different account types, and reshape aggregate emotional expression.

In this study, information entropy and information transfer entropy are introduced into the study of climate change information dissemination flow. Shannon introduced the idea of information entropy in 1938, and it is mostly used to address the issue of measuring information content. Computer science, statistical mechanics, physics, and other disciplines all made extensive use of information entropy theory [13]. Created by Schreiber [14], transfer entropy, also known as transfer information, is a dynamic and asymmetric measure that is based on the Shannon entropy theory. By identifying the asymmetry in the way the two processes interact, this measure seeks to ascertain the directionality of information transferred between them [14,15]. Transfer entropy, a dynamic, asymmetric measure, has quantified information flow in time series [16], distinguished biomedical data [17], and analyzed financial markets [18–21]. Despite applications in opinion leader identification and network influence [22–24], its use in climate information dissemination flow remains unexplored.

The purpose of this study is to explore: the dynamic evolution characteristics of climate information communication flow (including attention flow, user flow and emotion flow) before and after China's dual-carbon target was put forward, the change of emotional tendency and its diffusion trend in the process of information communication, and the geographical and spatial differences of emotional response. (1) Attention flow analysis: Weibo's text is mined by LDA topic modeling, and the evolution path of public discussion topics before and after the announcement of the dual-carbon target is tracked, and the temporal and spatial changes of topic attention are visualized by a heat map. (2) User flow analysis: Combining user type identification and time series analysis, explore the dynamic and dominant changes of different types of users' influence in the information communication network. (3) Emotional flow analysis: The fine-grained emotional tendency is identified and calculated by combining BERT deep semantic model and HIT Dictionary of Information Retrieval Laboratory of Harbin Institute of Technology. On this basis, Information Entropy is introduced to quantify the disorder and fluidity of emotional state, and Transfer Entropy is used to analyze the directionality, intensity, and spatial difference patterns

of emotional information transmission between different user levels and different geographical regions, revealing the hierarchical structure and geographical coupling characteristics of emotional flow.

This study makes three main contributions. First, it develops a theoretically informed, multi-layer perspective on climate information communication: This study integrates attention flow, user flow, and emotional flow into a unified analytical perspective. By positioning the dual-carbon target as a macro-level policy signal, the framework connects changes in public attention, account participation, and emotional expression across platform dissemination layers. Second, it provides large-scale empirical evidence on how climate-related communication on Chinese social media differed before and after the announcement of the dual-carbon target. The analysis connects a macro-level policy signal with changes in online topic composition, account participation, and aggregate emotional expression across platform dissemination layers. Third, the study operationalizes this multi-layer perspective through a complementary set of established computational methods. LDA is used to identify changes in thematic attention, BERT-based classification is used to describe emotion categories, and information entropy and transfer entropy are used to examine distributional uncertainty and predictive directional dependence.

The paper is structured as follows: Section 2 details methods (LDA, BERT, entropy measures) and data. Section 3 presents results (attention, user, information flow analysis). Section 4 discusses findings, limitations, and policy implications.

2. Methodology and Data

2.1. Data Acquisition, Cleaning, and Training Preparation

Data retrieval was organized around the search terms, observation period, and source platform. Drawing on the research context and the Handbook of Knowledge on Combating Climate Change, the retrieval terms are reported below in three thematic groups for clarity. General climate-related terms included “climate change”, “global warming”, “climate crisis”, “rising global temperatures”, “greenhouse effect”, “greenhouse gases”, “global warming potential”, and “extreme weather”. Policy- and carbon-management terms included “climate change policy”, “carbon emissions”, “energy conservation and emission reduction”, “afforestation”, “forest carbon sinks”, “carbon neutrality”, “carbon capture and storage”, “clean development mechanism”, “carbon tax”, “carbon tariffs”, “carbon trading”, “carbon verification”, and “inclusive carbon initiatives”. Green and low-carbon development terms included “green technology”, “green products”, “green consumption”, “low-carbon cities”, “low-carbon industries”, “low-carbon lifestyles”, and “carbon footprint”. A Python-based retrieval procedure was used to collect Sina Weibo posts published between June 2019 and November 2021. September 2020, when China announced its carbon-neutrality target, served as the dividing point between the two analytical periods.

The collected records were subsequently subjected to deduplication and text normalization. When records shared both the same username and textual content, only the chronologically earliest record was retained. HTML tags, redundant whitespace, and symbols without semantic content were removed. Records outside the thematic scope of climate change and those with geographic fields labeled “Overseas” or “Other” were excluded. After screening, 904,837 posts remained, comprising 17,380 original posts, 767,171 first-level retweets, and 120,286 second-level retweets. Because subsequent reposting from the second-retweet layer was rare, the dataset was limited to original posts and the first two retweet layers.

From the cleaned dataset, 11,902 climate-related posts were randomly selected from the original-post and retweet records for model development. Of these posts, 5902 were included in the training set, 1000 in the validation set, and 5000 in the test set, corresponding to 49.6%, 8.4%, and 42.0% of the climate-related labeled data, respectively.

Each selected climate-related post was manually assigned to one of six emotion categories: neutral, happy, angry, sad, fear, or surprise. Three graduate students served as annotators. Before formal annotation, the annotators received standardized training based on the emotion-category keywords contained in the HIT sentiment lexicon. The annotation was conducted in two rounds. In the first round, the three annotators independently assigned an emotion label to each post. In the second round, posts for which the initial labels were inconsistent were jointly reviewed and discussed by the three annotators until a consensus label was reached. The consensus labels obtained through this procedure were used for subsequent model development and analysis.

2.2. LDA Model

In Weibo topic mining, the data is modeled and assessed using the LDA topic model. This generation probability model, which was first presented by Blei et al. [25], is based on unsupervised learning and may be used to evaluate textual content and determine the probability distribution of each topic in the input document. Consequently, several recommender systems describe texts using the probability distribution of themes derived by

LDA [26–28]. The original posts were divided into two corpora according to whether they were published before or after the announcement of the dual-carbon target. Chinese word segmentation and stop-word filtering were performed before LDA estimation. The number of topics was determined with reference to the topic-coherence curves.

2.3. BERT Model

Sentiment analysis, also known as opinion mining, identifies and quantifies emotional information expressed in text. To determine public opinion and user interest on a range of issues, it is useful to examine comments on social media posts, product reviews, movie reviews, and other sources [29]. Google submitted BERT, a pre-trained language model built on the Transformer architecture, in 2018 [30]. It is an expert deep-learning method that has shown excellent sentiment analysis performance [31]. BERT can extract powerful data features. The method is proficient at obtaining time-varying characteristics from the composite data, enabling it to precisely forecast the composite data within a particular time frame in the future [32]. In contrast to conventional language models, the BERT model makes use of a bidirectional Transformer encoder that may simultaneously use contextual information to improve sentence-level word interpretation. The BERT model goes through two steps of pre-training: Next Sentence Prediction (NSP) and Masked Language Model (MLM). In the machine learning stage, words that are randomly masked in the input phrases are predicted by the BERT model based on contextual information. In the NSP stage, the BERT model establishes whether two sentences are continuous. The basic idea behind BERT is to learn a generalized language representation through large-scale unsupervised pre-training, followed by supervised fine-tuning to adapt to a particular task. BERT is essentially a stack of multiple Transformer structures with an additional segment embedding in the embedding part [30]. A deep bidirectional language representation is created by training the BERT model on a contextual corpus of text using a masked language model, which addresses the drawbacks of traditional unidirectional language models [33]. To create a deep bidirectional language representation, Joshy and Sundar [29] compared BERT, DistilBERT, and RoBERTa for sentiment analysis and reported that BERT outperformed the other two models on the datasets used in their study. In this study, BERT is used to assess the public's sentiment inclination toward climate change, a pre-trained language model. Figure 1 depicts the BERT model's structure:

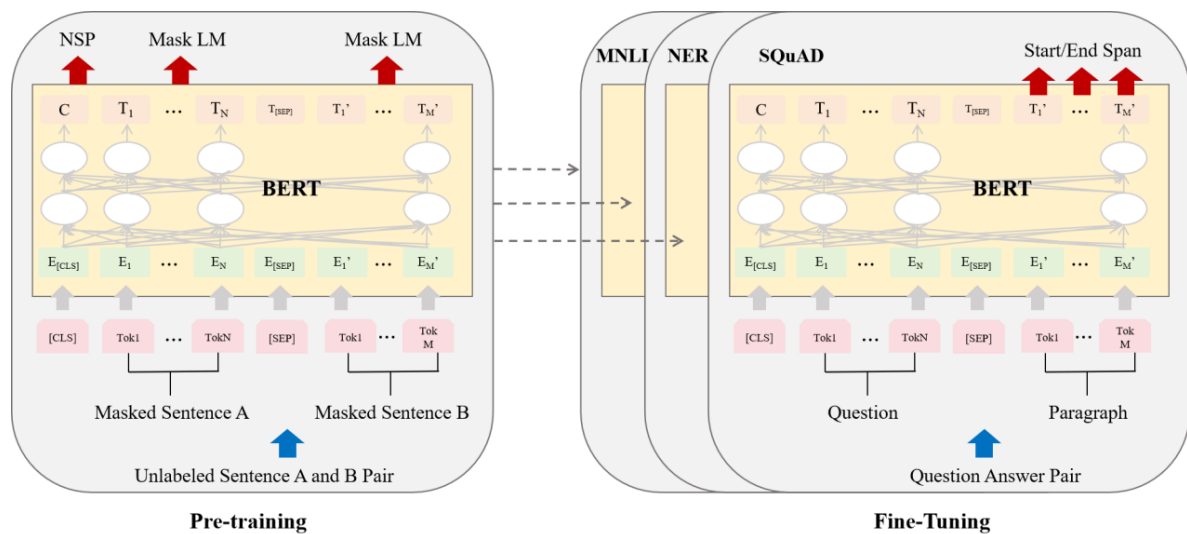


Figure 1. BERT model structure.

The annotated dataset used in this study comprised two parts. The first consisted of posts randomly selected from the crawled data, while the second was a general-domain Weibo dataset provided by the Research Center for Social Computing and Information Retrieval at Harbin Institute of Technology. The raw data for the latter were collected from Sina Weibo and supplied by the Micro Hotspot Big Data Research Institute. The training set contained 5902 randomly selected posts from the crawled data and 27,768 general-domain posts from the HIT dataset. The validation set contained 1000 randomly selected posts from the crawled data and 2000 general-domain posts from the HIT dataset, while the test set contained 5000 randomly selected posts from the crawled data. Following model training, an accuracy of 89% was achieved on the test set.

Detailed class-wise results are presented in Table 1.

Table 1. Classification performance on the climate-specific test set.

Emotion	Precision	Recall	F1-score	Support
Angry	0.83	0.98	0.90	366
Fear	0.91	0.91	0.91	43
Happy	0.97	0.67	0.79	1257
Neutral	0.87	0.98	0.92	2970
Sad	0.94	0.75	0.83	269
Surprise	0.85	0.91	0.88	95
Macro avg	0.89	0.86	0.87	5000
Weighted avg	0.89	0.88	0.88	5000

2.4. Information Entropy

Shannon first proposed the concept of information entropy in 1938, primarily to address the issue of measuring information content. Information entropy is a common way to express information quantity in information theory. The degree of information confusion is typically gauged using information entropy. The entropy value and the degree of information confusion are directly correlated; the higher the value, the more confused the situation is. Information entropy is a relatively new notion in information science that has been applied and popularized through study. Usually, information entropy is used to judge whether the system is orderly. As the randomness increases, the system distribution will become more and more chaotic and the information entropy will increase. Conversely, when the randomness is smaller, the information entropy is lower. With the decrease of system randomness, it increases, its distribution is more orderly, and the information entropy decreases. Therefore, the source can be regarded as a random variable. Information entropy solves the problem of random event information through probability theory and mathematical statistics. The information entropy $H(X)$ is calculated as follows:

$$H(X) = - \sum_{i=1}^n P_i(X_i) \log_b P_i(X_i) \quad 0 \leq P_i \leq 1, i = (1, 2, \dots, n) \quad (1)$$

where: H represents the information entropy of the information source. X_i represents a possible random event (a message symbol or information primitive that the information source may contain), and P_i represents the probability of occurrence of the event. Since $0 \leq P_i \leq 1$, $\log_b P_i(X_i)$ is negative, the information entropy should be positive if the formula $\sum_{i=1}^n P_i(X_i) \log_b P_i(X_i)$ is preceded by a negative sign. The information entropy is positive, and its unit is determined by b in the formula, and the value of b is determined by the nature of the information source. When $b = 2$, it means that there are two kinds of random events in the information source, and bits are the unit of information entropy. The unit of information entropy is nats when $b = e$. The unit of information entropy is dits when $b = 10$. Similar to the concept of thermodynamic entropy of thermodynamic systems, information entropy introduces uncertainty and chaos to measure the information content in the process of information dissemination. The difference is that the information entropy may not be equal to probability.

The study's statistics on the climate change blog posts' emotional inclination in different periods are substituted into the formula, and the information entropy change trend of the emotional tendency of netizens in different periods is obtained. Therefore, $P_i(X_i) = \frac{X_i}{\sum_{j=1}^n X_j}$, that is, the probability of a random occurrence of an event, is the ratio of the frequency of the current event to the frequency of all similar events. In the calculation process, we must first determine the values of different emotional tendencies, then solve the probability of each emotional tendency, and then, based on the assumption that b has a value, compute the relevant information entropy using the related formula.

2.5. Information Transfer Entropy

Transfer entropy has been seen to be an essential instrument for analyzing causality in nonlinear systems since Schreiber introduced the idea in 2000 [34]. According to Montalto et al. [35], it can identify directional and dynamic information, but it does not employ a particular function form to explain the relationship between various variables. Information transfer entropy is a statistic that quantifies the information flow's direction and intensity in time series data. For two given Markov time series processes, let x and y be two discrete time series with marginal probability $P(x)$ and $P(y)$, and their joint distribution probability is $P(x,y)$. Kullback and Leibler's [36] distance model quantifies the information flow between them, and the joint entropy is:

$$H(X, Y) = - \sum_{x \in X} \sum_{y \in Y} P(x, y) \log P(x, y) \quad (2)$$

Given x , the conditional entropy of uncertainty of y is:

$$H(Y | X) = - \sum_x \sum_y P(x, y) \log P(y | x) \quad (3)$$

In terms of the variation in conditional entropies, the Transfer Entropy is defined as follows:

$$TE(X \rightarrow Y | Z) = H(Y^F | Y^P, Z^P) - H(Y^F | X^P, Y^P, Z^P) \quad (4)$$

This is recast as the total of the Shannon entropies:

$$TE(X \rightarrow Y) = H(Y^P, X^P) - H(Y^F, Y^P, X^P) + H(Y^F, Y^P) - H(Y^P) \quad (5)$$

In this case, Y^F is a forward-shifted version of Y with a lag of Δt concerning the previous time series X^P , Y^P and Z^P . In this paradigm, we state that, with respect to side information Z , X does not G-cause Y unless and until $H(Y^F | Y^P, Z^P) = H(Y^F | X^P, Y^P, Z^P)$, or when $TE(X \rightarrow Y, Z^P) = 0$, holds true.

In addition, because the transfer entropy is directional, the transfer entropy from X to Y is not equal to that from Y to X , so we can define the net outflow of information: we can interpret this quantity as the main direction of information flow. In other words, if the result of the above equation is greater than 0, it displays which system provides additional prediction data regarding a different system, or it indicates which direction the information traveling from X to Y is more dominating than the other. It has been demonstrated by Barnett et al. [37] that if every variable has a joint Gaussian distribution, then linear Granger causality and transfer entropy are equal.

3. Data Analysis

3.1. Attention Flow Analysis

3.1.1. Topic Analysis before Putting forward the Dual-Carbon Target

Based on the LDA topic analysis findings, before the dual-carbon target's implementation, the public mainly paid attention to seven climate change topics, namely Topic 1-1 (low carbon and sustainable development), Topic 1-2 (green travel and energy conservation and environmental protection), Topic 1-3 (extreme weather and biological extinction), Topic 1-4 (carbon emission reduction and public welfare reporting), Topic 1-5 (climate change report and urban low carbon), Topic 1-6 (energy and peak carbon), and Topic 1-7 (ecological environment and climate crisis).

It can be seen from Figure 2a that Topic 1-5 (climate change report and urban low carbon) is the most discussed topic. According to the analysis of the topic sentiment tendency in Figure 2b, in the analysis of non-neutral emotion tendency, the happy emotion of each theme accounts for the largest proportion, among which the positive emotion of Topic 1-2 accounts for a relatively high proportion, while the negative emotion of Topic 1-1, Topic 1-3, Topic 1-6 and Topic 1-7 accounts for a relatively high proportion. Figure 2c illustrates that with time, the degree of attention to different topics has been changing, among which the degree of discussion on various topics is greater in December 2019.

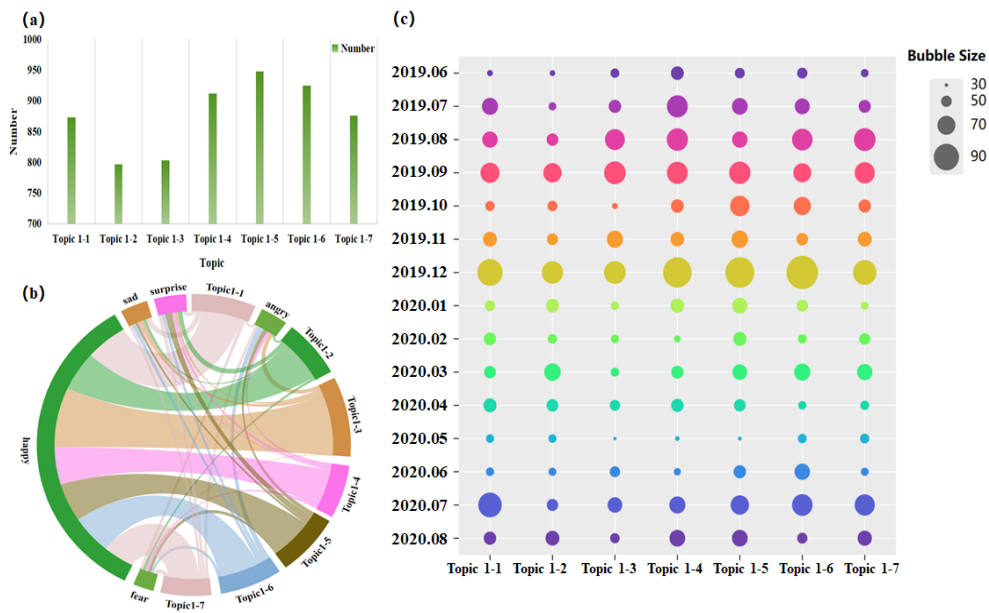


Figure 2. Topic analysis before the dual-carbon target's implementation. (a) Attention to different topics. (b) Sentiment analysis of seven climate change topics. (c) Topic heat map.

3.1.2. Topic Analysis after Putting forward the Dual-Carbon Target

According to the results of LDA topic analysis, following the implementation of the dual-carbon target, the public mainly paid attention to seven climate change topics, namely Topic 2-1 (photovoltaic market and energy strategy), Topic 2-2 (carbon neutral and low-carbon cities), Topic 2-3 (weather warming and temperature increase), Topic 2-4 (international climate strategy) and Topic 2-5 (climate crisis and popular science), Topic 2-6 (peak carbon and new energy), and Topic 2-7 (melting glaciers and climate change).

It can be seen from Figure 3a that Topic 2-2 is the most discussed, namely carbon neutrality and low-carbon cities. According to the analysis of theme emotion tendency in Figure 3b, in the analysis of non-neutral emotion tendency, the happy emotion of each theme accounts for the largest proportion, among which the positive emotion of Topic 2-2 accounts for a relatively high proportion, while the negative emotion of Topic 2-3, Topic 2-5 and Topic 2-6 accounts for a relatively high proportion. It can be seen from Figure 3c that with time, the attention on different topics has gradually increased.

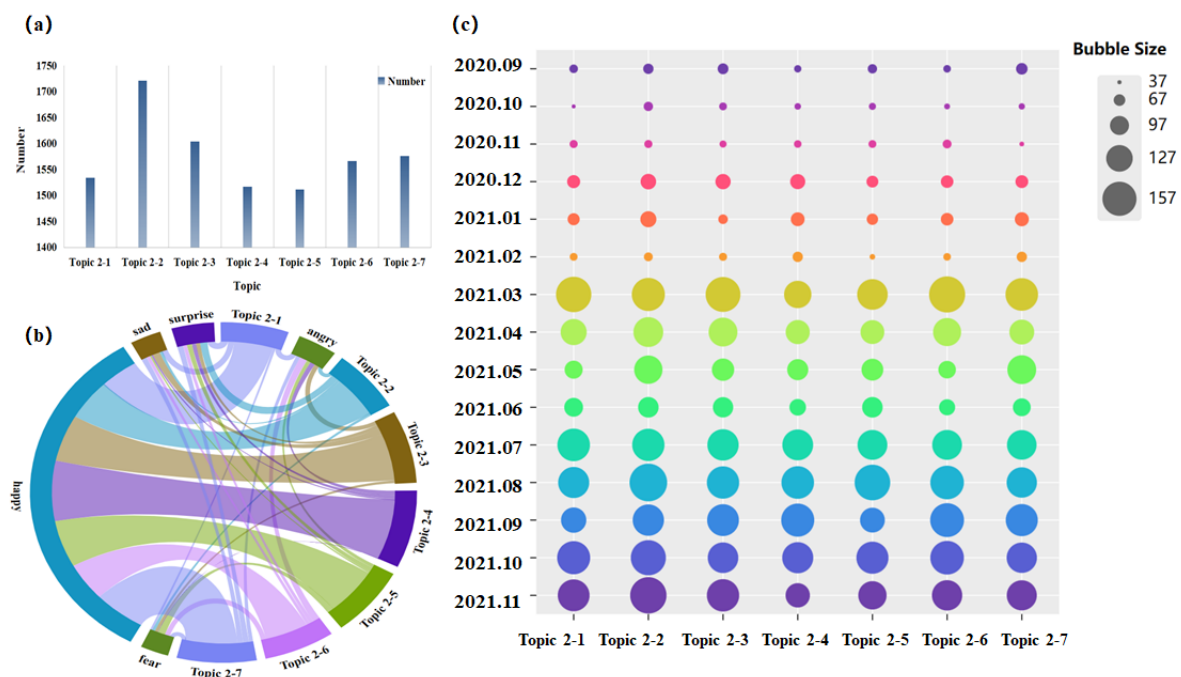


Figure 3. Topic analysis following the implementation of the dual-carbon target. (a) Attention to different topics. (b) Sentiment analysis of seven climate change topics. (c) Topic heat map.

3.2. User Flow Analysis

3.2.1. Spatio-Temporal Characteristics of Users

User types were identified from the account-category labels contained in the collected Weibo user information. The categories represented in the analysis included regular users (C), celebrities (F), government users (G), corporate users (E), media users (M), university users (S), group/institution users (T), junior talent users (J), and middle-level and senior-level talent users (A).

Figure 4 illustrates that, generally speaking, the three main user categories—celebrity, government, and media users—post more posts, are in the majority, and are crucial. There has been a consistent and modest amount of posts from group (organization) users, university users, corporate users, and regular users. Government users were quite engaged from the time of posting, before the formal proposal of the dual-carbon target. Following the announcement of the dual-carbon target, more posts were made by different user types—nearly all of them had 100 or more—and famous users' activity surged dramatically. Simultaneously, there has been an increase in postings issued by certain corporate users, though not by more than 100.

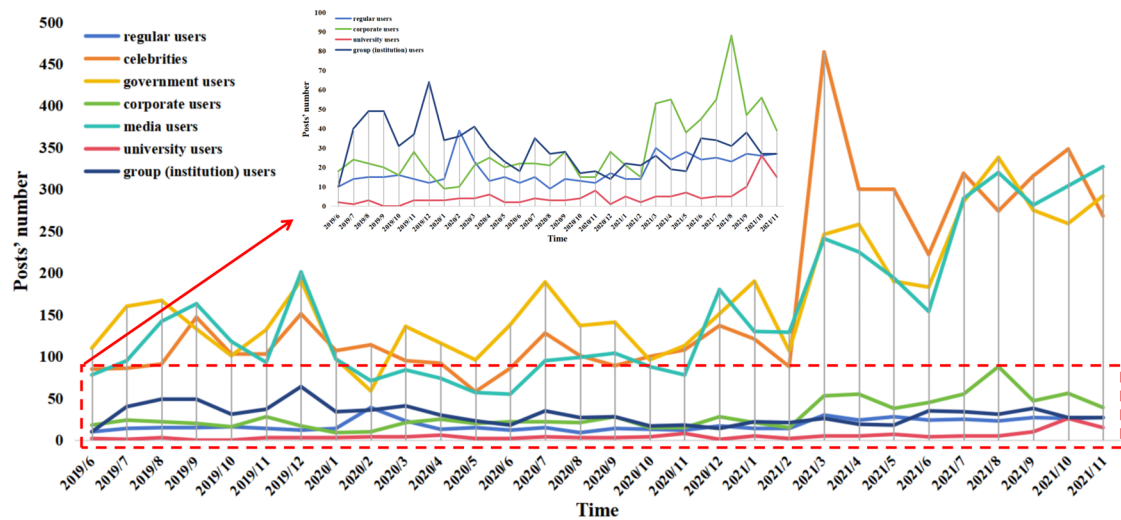


Figure 4. Number of original blog posts for different types of users.

3.2.2. User Emotional Flow

Based on the established user-type classification, this study further selected the seven user categories with the highest total posting volumes, ranked according to the total number of Weibo posts contributed by each category in the dataset. Posts published by these user categories across the different information-dissemination layers were then extracted for emotion analysis. User categories with lower posting volumes contained relatively sparse observations and were therefore unsuitable for meaningful category-level analysis. By contrast, the seven leading user categories accounted for the majority of posts in the dataset and encompassed a diverse range of actors, including individuals (ordinary and celebrities), official institutions (government and media users), commercial actors (corporate users), educational institutions (university users), and social organizations (group/institution users), thereby providing broad representation. Based on the resulting ranking, the seven selected user categories were regular users (C), celebrities (F), government users (G), corporate users (E), media users (M), university users (S), group/institution users (T), junior talent users (J), and middle-level and senior-level talent users (A).

Based on the six-category emotion-classification results, Figure 5 compares the five non-neutral emotion categories—angry, fear, happy, sad, and surprise—across user types and information-dissemination layers before and after the announcement of the dual-carbon target. Neutral remains part of the six-category classification framework and is included in the overall model evaluation, whereas Figure 5 presents the five non-neutral categories.

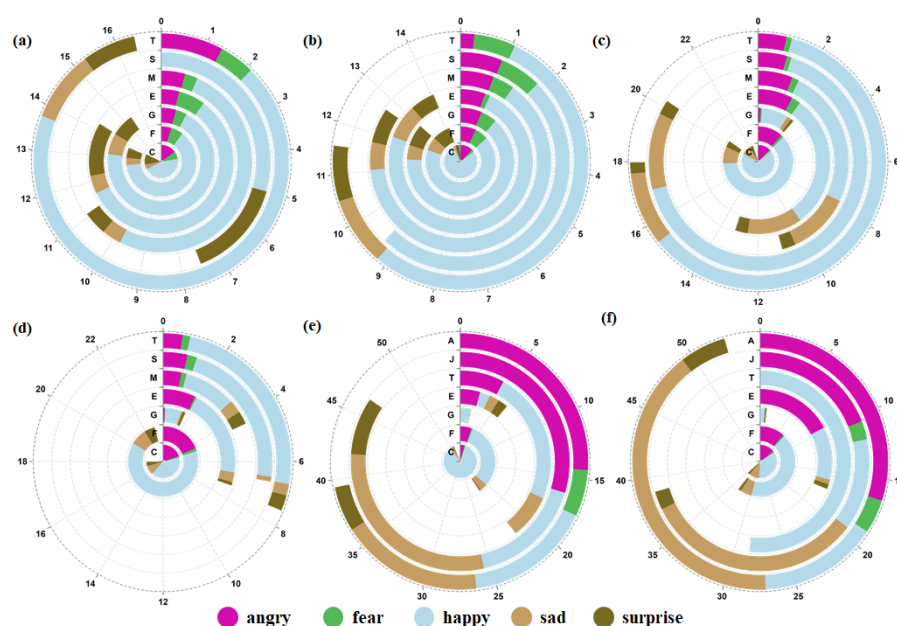


Figure 5. User emotion categories by user type and information layer before and after the announcement of the dual-carbon target. (a) Original-post layer: pre-announcement; (b) Original-post layer: post-announcement; (c)

First-retweet layer: pre-announcement; (d) First-retweet layer: post-announcement; (e) Second-retweet layer: pre-announcement; (f) Second-retweet layer: post-announcement.

In the original-post layer before the announcement of the dual-carbon target (Figure 5a), the angry category was highest among regular users, followed by group/institution users. Fear was highest among regular users, followed by corporate users. The happy category was highest among government users, followed by group/institution users, whereas sad was highest among group/institution users, followed by government users. Surprise was highest among university users, followed by corporate users. After the announcement of the target (Figure 5b), angry remained highest among regular users, followed by celebrities. The proportion of fear did not exceed 1% for any user type. Happy was highest among regular users, followed by corporate users; sad was highest among corporate users, followed by group/institution users; and surprise was highest among celebrities, followed by group/institution users.

In the first-retweet layer before the announcement (Figure 5c), angry was highest among regular users, followed by celebrities. The proportion of fear did not exceed 0.5% for any user type. Happy was highest among regular users, followed by university users, while sad was highest among corporate users, followed by university users. The proportion of surprise did not exceed 0.5% for most user types. After the announcement (Figure 5d), angry was highest among regular users, followed by celebrities, and the proportion of fear did not exceed 0.5% for any user type. Happy was highest among celebrities, followed by regular users, whereas sad was highest among regular users, followed by celebrities. Within the surprise category, celebrities recorded the highest proportion, followed by regular users.

Before the announcement in the second-retweet layer (Figure 5e), junior talent users recorded the highest proportions in the angry (16.28%) and sad (16.28%) categories, followed by middle-level and senior-level talent users, whose corresponding proportions were 14.33% and 9.96%. Fear was highest among middle-level and senior-level talent users at 3.23%, while the proportions for the other user types did not exceed 0.5%. Happiness was highest among regular users, followed by celebrities. Surprise was highest among junior talent users at 4.65%, followed by middle-level and senior-level talent users at 3.13%.

After the announcement in the second-retweet layer (Figure 5f), middle-level and senior-level talent users recorded the highest proportions in the angry (16.47%) and sad (22.16%) categories, followed by junior talent users at 10.45% and 17.91%, respectively. Fear was highest among middle-level and senior-level talent users at 2.34%, followed by junior talent users at 1.49%. In the happy category, group/institution users recorded 28.57%, whereas celebrities recorded 23.10%. Surprise was highest among middle-level and senior-level talent users at 3.22%, followed by junior talent users at 1.49%.

Overall, the user type with the highest proportion differed across emotion categories, periods, and information layers. In the second-retweet layer, junior and middle-level and senior-level talent users recorded the highest proportions in the angry and sad categories before and after the announcement, respectively. These category-specific results provide a more detailed description of the patterns presented in Figure 5.

3.3. Emotional Flow Analysis

3.3.1. Information Entropy and Emotional Transfer

The information entropy of different information layers shows great changes, among which the original layer is the most stable and the forwarding layer is the most volatile, indicating that the more information spreads, the degree of information confusion increases with increasing uncertainty, by the law of entropy rise. When analyzing the information transfer entropy between different emotions in microblogs, we first need to classify the emotional state of microblog text, and then calculate the information transfer entropy between pairs of emotional categories across different information layers.

From Figure 6a, before the dual-carbon target's proposal, in the original layer, surprise shifts more to sad, followed by anger; the emotion of sad is more or sad, followed by neutral; neutral shifts more to happy; the emotion of happy is more or happy, followed by angry; and the changes of fear are more extreme, flowing almost exclusively to happy or surprise; and angry switches most to happy. From Figure 6b, following the proposal of the dual-carbon target, the original layer of surprise flows to angry and sad; sad flows to happy and neutral; neutral flows more to sad; happy also flows more to sad; fear flows more to angry; and angry flows more to sad.

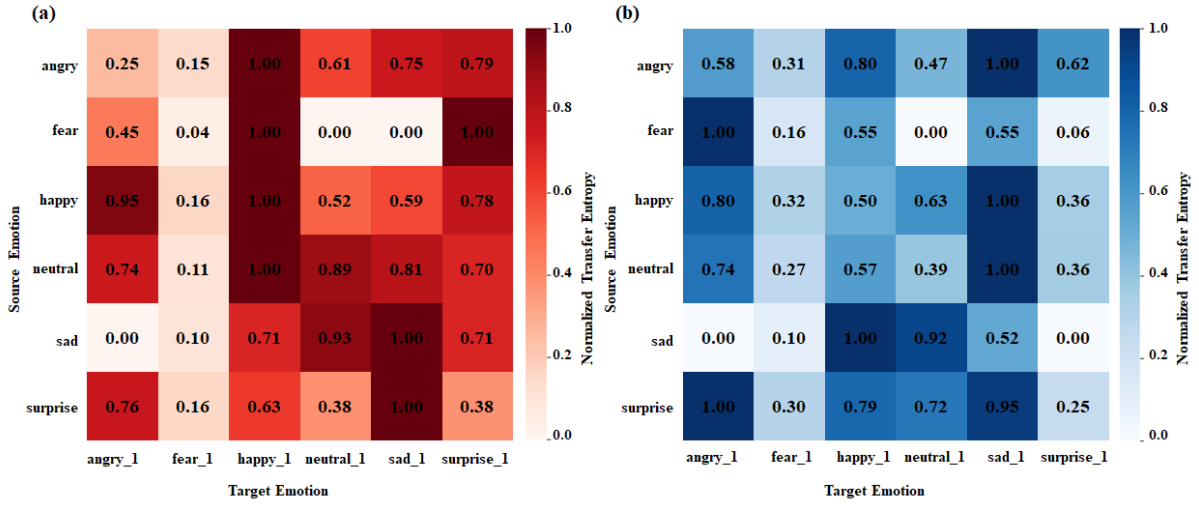


Figure 6. Transfer entropy heatmap (a) Pre-Target Transfer Entropy; (b) Post-Target Transfer Entropy.

From this, we have observed a phenomenon. When it comes to the flow and distribution of climate-related information, stronger directional patterns from positive toward negative emotion categories were observed in parts of the dissemination process, while reverse patterns were also present. This shows that in the process of information flow, information has a certain public opinion orientation. Although emotions will be gradually strengthened due to emotional effects, the direction of strengthening is not necessarily positive, which requires higher effectiveness in disseminating information.

3.3.2. Emotional Time Series Evolution

Figure 7a,c depict the analysis of the sentiment orientation of blog posts before and after the implementation of the dual-carbon target, and to visualize the proportion of the sentiment orientation more intuitively, the figure shows the proportion of the non-neutral sentiment orientation. Figure 7b,d depict the proportion of the sentiment orientation of different information layers before and after the implementation of the dual-carbon target.

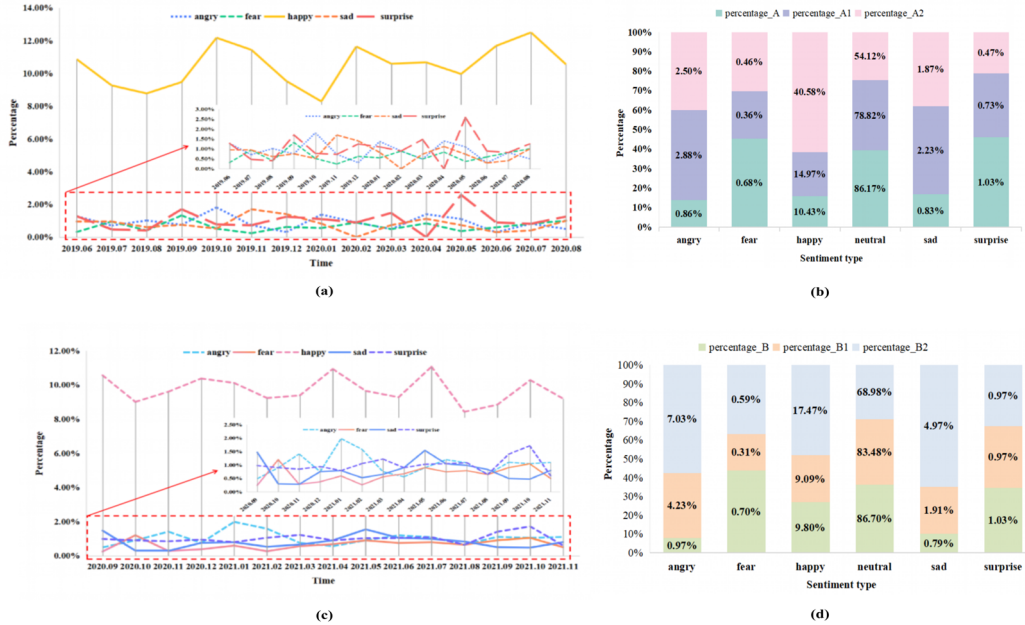


Figure 7. Emotional time series evolution. (a) Pre-Dual-Carbon Sentiment Orientation: Original Posts; (b) Pre-Dual-Carbon Emotional Flow: Multi-Tier Cascade (O, F1, F2); (c) Post-Dual-Carbon Sentiment Orientation: Original Posts; (d) Post-Dual-Carbon Emotional Flow: Multi-Tier Cascade (O, F1, F2).

Figure 7b illustrates before the dual-carbon target's implementation, in the process of emotional flow, the emotion of anger was increasing, the emotion of neutrality was decreasing, and emotions were strengthened to

some extent. It can be seen from Figure 7d that after the implementation of the dual-carbon target, in the process of emotional flow, the angry and sad categories were more prevalent, the emotions of neutrality decreased, and the emotions were strengthened to some extent. Compared with before the dual-carbon target's implementation, the individual's sentiment orientation toward climate change was more profound following the implementation of the dual-carbon target.

3.3.3. Geographical Emotional Differences

Additionally, the percentage of non-neutral specific sentiment orientation was examined before and after the dual-carbon target was implemented in various locations and information layers. Figure 8 presents the geographic distribution of climate-related posts with available provincial information and the distribution of non-neutral emotional expressions across dissemination layers. Background shading indicates the number of posts recorded in each province, while the accompanying bar charts show the proportions of the non-neutral emotion categories. The figure therefore describes spatial patterns in the platform activity captured by the dataset rather than directly ranking regional climate awareness or climate-risk perception.

Regardless of when the dual-carbon target was suggested, Figure 8 shows how the amount of blog posts in various information layers across different regions tends to concentration to diffusion. It also shows that in comparison to the northern region, the southern region of China shows increased worry about climate change. Coastal locations have a higher degree of climate concern than inland places. Figure 8 highlights the variations in sentiment orientation that are not neutral in different places. No matter whether in different periods or in different information layers (original-forwarding 1, forwarding 2), we can see the changes in Sentiment orientations. On social networks, emotional contagion is faster, wider, and deeper than we thought.

It can be further found that (1) before the dual-carbon target's implementation: (i) the proportion of non-neutral sentiments decreased in Qinghai, Ningxia, Shanxi, Jilin, and Tianjin during the originating layer-forwarding layer 1, mostly due to a decrease in positive attitudes toward climate information, such as happy sentiments, and an increase in negative attitudes, such as sad and angry sentiments. The cause of the proportion's growth of non-neutral emotions in Beijing, Liaoning, Zhejiang, Guizhou, Guangxi, Guangdong, Taiwan, and Jiangxi is due to an increase in the degree of discussion, a richer variety of emotion types, and a significant increase in both positive (e.g., happy) and negative (e.g., sad and angry) attitudes. (ii) In the process of forwarding layer 1 and layer 2, more non-neutral emotions emerged in more areas, mainly because happy emotions increased significantly. (2) Following the implementation of the dual-carbon target: (i) In the original layer, Ningxia possessed the greatest percentage of emotions that weren't neutral because of the high proportion of happy and surprised emotions. (ii) In the process of the original layer-forwarding 1 layer, the percentage of emotions that were not neutral in Ningxia decreased, and the percentage of emotions that were not neutral in Qinghai and Tibet rose because angry and sad emotions began to appear. (iii) In the process of forwarding layer 1 to layer 2, the percentage of emotions that are not neutral in all regions except Shandong increased because the emotional situation in these regions changed less, and even the emotions in some regions were strengthened.

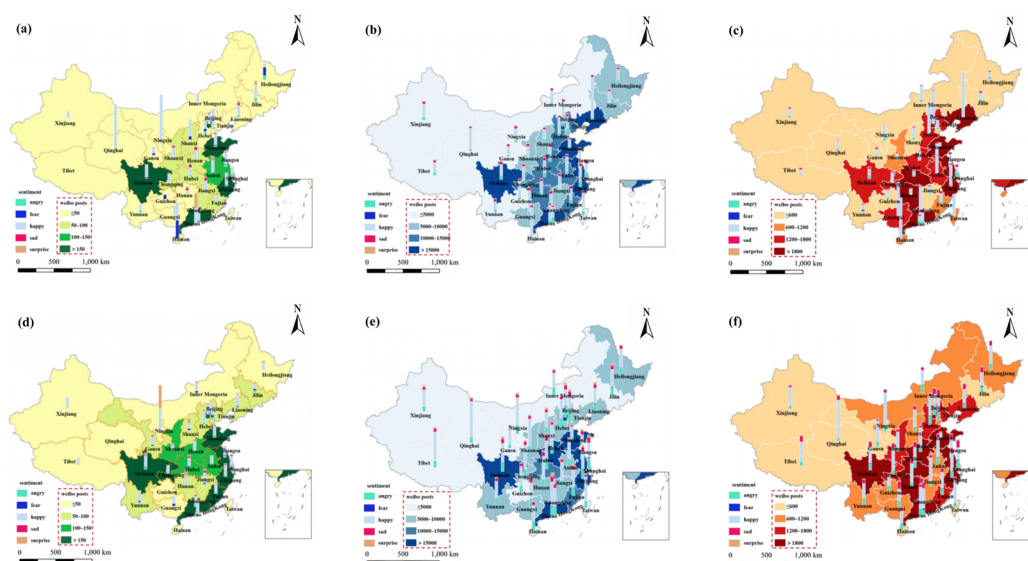


Figure 8. Geographic distribution of Weibo-post volumes and non-neutral emotion proportions across information-dissemination layers before and after the announcement of the dual-carbon target. (a) Original-post layer: pre-

announcement; (b) original-post layer: post-announcement; (c) first-retweet layer: pre-announcement; (d) first-retweet layer: post-announcement; (e) second-retweet layer: pre-announcement; (f) second-retweet layer: post-announcement.

4. Discussion

Weibo posts about climate change were crawled for this investigation, varying in informational depth. The climate change issues that the public was concerned about at different times, in different places, with different information levels, and with different sentiment flows of users were discovered through text mining and sentiment analysis. The data were analyzed using the LDA model and the model combining BERT and the sentiment dictionary of the Harbin Institute of Technology. The main findings and discussions are as follows:

- (1) Regarding attention flow, policy drives public issues from “climate reporting” to “carbon neutral practice”, but negative emotions rise with the implementation of policies, reflecting public concerns about implementation challenges (such as transformation costs). This is consistent with the emotional arousal mechanism of extreme weather events [38]. Before and following the dual-carbon target’s implementation, the public’s main concerns about climate change were seven topics. (i) Before the dual-carbon target’s implementation: low carbon and sustainable development, green travel and energy conservation and environmental protection, extreme weather and biological extinction, carbon emission reduction and public welfare reporting, climate change reporting and urban low carbon, energy and peak carbon emissions, ecological environment, and climate crisis. Among them, climate change reports and urban low carbon are the most discussed topics. Among the non-neutral sentiment orientations of this topic, happy accounts for the largest proportion (9.92%), followed by surprise (1.79%) and angry (1.05%). (ii) Following the implementation of the dual-carbon target: photovoltaic market and energy strategy, carbon neutral and low-carbon city, climate warming and temperature increase, international climate strategy, climate crisis, and popular science, peak carbon emissions and new energy, glacier melting and climate change. Carbon-neutral and low-carbon cities are much discussed. Among the non-neutral sentiment orientations of this topic, happy accounts for the largest proportion (9%), followed by surprise (1.42%). Low-carbon cities are the subjects of most concern. Natural calamities, such as extreme weather brought on by climate change, are also subjects of ongoing public discussion and worry. Given the social context, it is easy to comprehend how urban adaptation might support resilience and sustainable development, as affirmed by the Intergovernmental Panel on Climate Change in its Fifth Assessment Report [39]. Due to the concentration of infrastructure and population in metropolitan regions, cities are the most important locations for climate action. They are at the vanguard of creating adaptation plans and strategies due to their increased understanding of the implications of climate change, and they are becoming more and more significant in incorporating climate change adaptation measures into the current framework of policy. As a result, there has been more conversation around this topic.

Researchers discovered that waves of heat and cold significantly influenced the attitude and frequency of Weibo topics in 2021 regarding climate change’s impact on extreme weather events, based on data from the China Meteorological Bureau’s China Climate Bulletin. In contrast to the baseline period, which was investigated two weeks before and two weeks after the disaster, there were more Weibo posts during the extreme weather events [40]. Moreover, “global warming” affects people’s attitudes, either directly or indirectly, a well-known facet of climate change. Numerous research has confirmed that experiencing severe temperatures can cause negative feelings [41,42]. Consequently, there has been a lot of interest in this subject. Warmth, positive influence, and high arousal feelings are implicitly linked, according to prior research, whereas the term “cold” is connected to low arousal and negative emotions.

- (2) Regarding user flow, government/celebrity accounts dominate the agenda setting, but the emotional polarization between regular users and intellectuals at the forwarding level indicates hierarchical differences in aggregate emotional expression. It is necessary to be alert to the negative emotional amplification effect of high-knowledge groups. In the spread of sentiment flow, we need to pay attention to the sentiment orientations of regular users, celebrities, and talented users. Compared with other groups, their non-neutral sentiment orientations towards climate information account for more. In addition, when the information is forwarded to a certain level, more talented users emerge, and their feelings are more profound. Before and following the dual-carbon target’s implementation, the emotion of anger increased while the emotion of neutrality decreased, and emotions were strengthened to some extent. Following the implementation of the dual-carbon target, in the process of emotional flow, the emotions of anger and sadness increased, while the emotions of neutrality decreased, and the emotions were strengthened to some extent. Compared with before the dual-carbon target’s implementation, the individual’s sentiment orientation toward climate change was more profound following the implementation of the dual-carbon target. Before and after the dual-carbon

target's implementation, the proportion of non-neutral emotions in different regions and different information layers increased. We need to pay attention to the changes in non-neutral sentiment orientations in various regions, whether in different periods or different information layers (original-forwarding 1–forwarding 2), we can see the changes in sentiment orientations. On social networks, emotional contagion is faster, wider, and deeper than we thought. This aligns with the findings of earlier studies. Because of the nation's frequent catastrophic weather events, more Chinese people are becoming conscious of climate change [43]. In China, the “silent majority” started taking an active part in online discussions on climate change, displaying a quick increase in both positive and negative feelings, according to Shen & Wang's [44] research. Li et al. [10] examined how residents who were using social media during an emergency rescue responded. Positive emotions are more widely dispersed than negative ones, which are less so. It was also discovered from examining the feelings posted on social media that people are very worried about how accurately and successfully information will be disseminated. When sharing information on social media, individuals hardly ever show their feelings, and some even adopt a pessimistic stance in the wake of tragedies. The network's emotional flow demonstrates the traits of cyclic amplification. Finally, the emotional bond created when two people cross paths on Weibo can instantly propagate throughout a vast area and swiftly establish a spectacular social structure. From the tiniest social scene where two individuals meet by coincidence to the quick realization of great social structure and emotional unification through instantaneous large-scale diffusion on the Internet, it is becoming more and more typical for Weibo [12]. Social media has rapidly increased both positive and negative emotions and, in reality, allows the “silent majority” to freely express their subjective thoughts.

- (3) Regarding emotional flow, the transformation from positive emotion to negative emotion in information dissemination is consistent with the “emotional cycle effect” of social media [45]. Geographical differences show that climate risk perception and emotional response are spatially coupled [46]. The number of blog posts in various information layers across different regions exhibits a trend from concentration to diffusion, regardless of when the dual-carbon target was proposed. At the same time, the central region exhibits a higher level of climate concern than the northeast, northwest, and southwest regions. China's southern area exhibits greater climate worry than its northern counterpart. Coastal regions exhibit greater climate worry when compared to inland locations. Furthermore, in the process of disseminating and flowing information about climate change, positive emotions turn more into negative emotions from the original layer to the forwarding layer, while some negative emotions turn to positive emotions instead, which shows that in the process of information flow, information has a certain public opinion orientation. Although emotions will be gradually strengthened due to emotional effects, the direction of strengthening is not necessarily positive, which requires higher effectiveness of information dissemination.

With the increased usage of social media, it has emerged as a valuable information resource for studying public opinion on social issues [47,48]. Social media and advances in big data and Internet technology have facilitated new forms of citizen participation in social governance [49]. They may also easily share information, access news sources, and express their thoughts on a range of social media channels [45,50,51]. All of these activities contribute to the promotion of sustainable development [52]. Concern over climate change among the general public may indicate that people are prepared to adopt modest lifestyle adjustments to lessen its effects [53,54]. China, one of the biggest economies in the world and a major emitter of greenhouse gases, has pledged to become carbon neutral by 2060 and reach a peak in emissions by 2030. This pledge demonstrates China's resolve to slow down global warming and sparks an unparalleled rise in domestic awareness of the issue [55]. This is in line with the study's result. It is certainly excellent news for reducing climate change that people are becoming more concerned about it on social media sites. The idea of ecological modernization holds that environmental governance and sustainable development are significantly influenced by public concern, which functions as an informal regulation [56]. This is mostly because being in the public eye will influence one's intentions and even real conduct [57,58]. People are more likely to adopt and support environmentally friendly practices and laws when they are aware of the environmental crisis and its possible negative impacts [59].

Different from the traditional media platform, the social media platform similar to Sina Weibo has built a new type of information node structure and node cluster, and the role and status of traditional media have “fallen” to the same position as individuals and become nodes in the complicated network. This node structure enhances the connectivity among netizens. Different nodes gather quickly because of common concerns. Some nodes become the core of content originality, while some nodes act as “porters” of information between different communities, forming a public space with extremely rapid information exchange. Because of this node structure, the public sentiment flowing between network fields is rapidly diffused, strengthened, and re-aggregated, forming a group-polarized view and consciousness.

Several limitations of the spatial analysis should be noted. Regional post volumes were not normalized by the number of active Weibo users or other measures of platform exposure because reliable province-level denominators were unavailable in the dataset. Population size, internet penetration, economic development, regional platform activity, and users' willingness to disclose geographic information may all affect the observed distribution of posts. Future research could combine social-media data with regional demographic and digital-access indicators to examine whether these geographic patterns remain after structural differences are considered.

5. Implications

5.1. Theoretical Implications

This study offers three theoretical implications. First, it conceptualizes climate communication as a multi-layer process involving the simultaneous reorganization of thematic attention, participating account types, and aggregate emotional expression. This framework connects dimensions that are frequently examined separately in social-media research. Second, it positions the announcement of the dual-carbon target as a macro-level policy signal within the platform communication environment. The temporal comparison illustrates how a major policy announcement can serve as an analytical breakpoint for examining changes in online climate discourse. Third, it extends climate communication research by incorporating platform dissemination layers and differentiated account types into the analysis of emotional expression. By examining how emotional distributions vary across original-post and retweet layers and among user categories, the study highlights the hierarchical and dynamic characteristics of climate information communication on social media. The theoretical contribution therefore lies in connecting macro-level policy signals, platform-layer structures, and differentiated patterns of user participation and emotional expression.

5.2. Practical Implications

Based on the empirical findings, the following policy actions are proposed: Governmental and corporate entities should actively collaborate with key social media influencers to disseminate climate information. Crucially, leveraging the observed “resonance effect”, these partnerships should be strategically designed to amplify evidence-based narratives promoting low-carbon behaviors, ensuring communication remains engaging, objective, and independent of specific agendas to foster informed public discourse. Our analysis confirms significant emotional contagion within social network information flows, characterized by heightened affective responses during climate communication. While this phenomenon presents an opportunity to enhance public awareness and motivate pro-environmental action through transparent disclosure of climate realities, it necessitates vigilant monitoring. Specifically, public agencies must implement mechanisms to detect and mitigate emotional polarization, particularly within secondary dissemination layers (L1/L2 forwarding tiers), and develop targeted interventions for highly educated cohorts identified as susceptible to polarized sentiment. Concurrently, robust measures are essential to counter misinformation and prevent contagion from escalating into societal anxiety or panic. Given the pronounced concentration of climate concern in coastal and southern regions, policy efforts must bridge the cognitive gap observed in inland populations. This requires enhancing climate literacy through expanded educational initiatives and diversified information channels. Critically, communication strategies must be distinctly tailored for climate-vulnerable regions (e.g., southern and coastal areas), employing emotionally resonant messaging calibrated to address localized risk perceptions and anxieties to effectively drive engagement and adaptive preparedness.

6. Conclusions

This study introduces the concept of climate information communication flow and employs transfer entropy and data mining techniques to analyze the attention flow, user flow, and emotional flow before and after China's dual-carbon target. Based on the analysis of the Chinese Weibo data, this study draws the following conclusions:

- (1) The introduction of the dual-carbon target shifted public discussion from general climate reporting to specific issues like carbon neutrality. However, policy implementation was accompanied by a rise in negative public emotions, reflecting concerns about practical challenges and costs.
- (2) Government and celebrity accounts dominate agenda-setting, but ordinary and talented users show stronger non-neutral sentiments during information dissemination. This reveals hierarchical differences in emotional contagion and highlights the risk of negative emotion amplification by talented groups.
- (3) The positive emotions in information communication are transformed into negative ones, which is consistent with the “emotional cycle effect” of social media. Geographical differences show that climate risk perception

and emotional response are spatially coupled.

- (4) Information diffusion first accelerates with time and then reaches saturation, and the increased information confusion conforms to the law of entropy increase. The result of information transmission entropy reveals the two-level transformation of diffusion mode and highlights the limitations of information dissemination.

Author Contributions

M.W.: Conceptualization; Methodology; Formal analysis & investigation; Writing—original draft preparation; Writing—review & editing. R.L.: Conceptualization; Funding acquisition; Supervision. J.N.: Formal analysis & investigation; Writing—review & editing; Supervision. W.L.: Writing—review & editing; Funding acquisition. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The data will be available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

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